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Three Essays on Digital Innovation from an Intellectual Property Rights Perspective

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BY

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ACCEPTANCE

This dissertation was prepared under the direction of **Zhitao Yin's** Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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This dissertation uses the lens of intellectual property rights (IPR) to challenge the Information Systems (IS) field's conventional view of a patent as a knowledge asset. It shows how IS scholars can leverage the IPR perspective to generate insights into digital innovation and how those insights can inform innovation policy, which establishes the regulatory governance framework for the digital innovation ecosystem.

Essay 1 aims to shift the focus of the literature on the production of digital innovation to the examination of digital patents. It surfaces (a) the critical beneficial influence of patent examiners' feedback—that is, why the claims of inventors' past applications have been rejected—on inventors' success in gaining subsequent digital patents and (b) how that benefit is subject to two key aspects of examiners' feedback—temporal and technological. Essay 1 therefore informs a debate among scholars and policy makers regarding the expertise of patent examiners in digital patents.

Essays 2 and 3 turn to the value creation of digital innovation, in which patent owners generate rent from their patents at the expense of social welfare. Specifically, Essay 2 joins the discussion on patent thickets—the overlapping of firms' IPR that may restrict their commercialization of their own inventions—while addressing the formation of patent thickets in the IT industry, in which firms are racing to assemble large patent portfolios. Results indicate that the knowledge spillover to competitors generated by a focal IT firm's patent disclosure can increase the level of patent thickets. Such impact depends on two key characteristics—the value of the focal firm's disclosure and the absorptive capacity of that firm's competitors. Essay 2 therefore uncovers the crucial role of disclosure for the optimal policy design to address patent thickets.

Essay 3 connects with the recent conversation on the role of crowdfunding in democratizing venture capital (VC) financing, while differentiating itself by addressing the IPR threat from a patent assertion entity (PAE), which is in the business of asserting digital patents. Results indicate that state anti-PAE laws are crucial in realizing two crowdfunding benefits: attracting VC investment into the state and diversifying the investments across industries within the state. Essay 3 thus surfaces the critical role that institutional governance of IPR risk plays in achieving crowdfunding benefits.

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Introduction

Digital innovation has radically changed the nature of new products and services and spawned novel pathways for the creation and appropriation of value (Nambisan et al. 2017). With innovation becoming increasingly dependent on software, digital patents are increasingly important for innovation in industries well beyond the traditional definition of electronics and information technology (IT). This shift attracts great interest from economists, strategic management scholars, and legal scholars, all of whom have a long tradition of examining innovation from the perspective of intellectual property rights (IPR). But it also offers a fantastic opportunity for information systems (IS) scholars, who have a unique contribution to make by generating interdisciplinary insights while making disciplinary contributions. Additionally, the IPR perspective offers the opportunity to broaden the focus of IS research on digital innovation from private-sector value creation to innovation policy, which establishes the regulatory governance framework for the digital innovation ecosystem.

An emerging discussion among IS scholars with respect to patents has mainly taken a knowledge perspective and explored the underlying mechanisms of generating patents and creating value from them (e.g., Joshi et al. 2010; Kleis et al. 2012; Ravichandran et al. 2017; Wu et al. forthcoming). However, patents are not merely a representation of knowledge. By providing inventors with a temporary period of market power by granting them IPR, patents aim to incentivize innovation by allowing inventors to recoup the fixed costs of their research investments. The patent office's examination of patent applications is therefore critical in the production of digital innovation, yet has not been considered in the scholarly discussion.

In addition, patents, once granted, may not actually encourage innovation, but rather generate significant deadweight loss (Williams 2017). Patent owners may leverage the market power of their patents to generate rent for themselves at the expense of social welfare. For example, IT firms are racing to assemble large patent portfolios to reserve a better position from which to commercialize their inventions. However, such actions collectively form a dense web of overlapping IPR—so-called patent thickets—in the IT industry, which distorts incentives to innovate and raises risks for competition and consumers (Federal Trade Commission 2012). It is therefore crucial to understand the mechanisms and contextual conditions of the formation of patent thickets in the IT industry in order to advance theory and empirical evidence of the mechanisms of patent thicket formation and to provide a robust basis for policy.

Recent years have seen an increasing problem of patent trolling (Cohen et al. 2016). A patent assertion entity (PAE)—a so-called patent troll—is in the business of buying, selling, and asserting digital patents. In fact, PAEs are responsible for a growing percentage of lawsuits in the IT industry (Federal Trade Commission 2012), making them a particularly salient risk factor in the financing and market viability of entrepreneurs. It is therefore important to take the risk of such deadweight loss from PAEs into account while understanding how digital innovations are financed and produced in the digital innovation ecosystem. The financing involves both venture capitalists and crowdfunding platforms, with the latter generating signals on potential investment opportunities for venture capitalists but also for PAEs. Understanding how signals from crowdfunding platforms affect the flow of venture capital, conditional on regulatory mechanisms to mitigate PAE risks, is therefore necessary to better understand effective governance of the digital innovation ecosystem.

By addressing these issues, the three essays in this dissertation take an important step in understanding the production and value creation of digital innovation through the lens of IPR.

In the first essay, I focus on the examination process for digital patents, in which patent examiners provide inventors with feedback with respect to innovativeness against their claims for IPR. By leveraging the history of the inventors with respect to the feedback received from US patent examiners in 2008–2017, I provide consistent evidence that examiners' feedback can reduce the chance of rejection for digital patent applications. Additionally, an inventor benefits more when the feedback is linked to temporally distant knowledge and to knowledge in diverse technology fields. This essay contributes to digital innovation by revealing the entire pipeline of the patent application process and the critical role of examiners' feedback.

Essay 2 aims to understand the formation of patent thickets in the IT industry. Specifically, what underlying mechanism establishes the IPR overlap among IT firms that may keep them from commercializing their inventions? With the enactment of the American Inventor's Protection Act (AIPA) in 2000, a firm must publicly disclose a patent application 18 months after filing. I outline two competing predictions on how pre-grant patent disclosure will affect the firm's IPR overlap with competitors: (a) a constraining influence due to patent examiners' evaluations that take the pre-grant disclosures into account while assessing competitors' patent claims and (b) knowledge spillover when technical information and market signals are revealed to competitors. To evaluate these competing explanations, I exploit a natural experiment: the enactment of AIPA. Results indicate that the knowledge spillover effect dominates, especially when the disclosure's technological value—that is, the extent to which the focal patent destabilizes the technological landscape (Funk and Owen-Smith 2017)—and the market value—that is, the stock market reaction to the grant of focal patent (Kogan et al. 2017)—are high. Moreover, the effect is more pronounced when the focal IT firm and its competitors are in similar technology spaces and product markets. This essay reveals the innovation interdependency among IT firms in terms of

IPR and uncovers the underlying mechanism by which it evolves. Thus, it provides more nuanced evidence of the dynamics of innovation in the IT industry.

Essay 3 takes into account crowdfunding platforms, such as Kickstarter, which are increasingly important for financing innovation and entrepreneurship and can generate high-quality signals that attract venture capitalists (VCs) to new regions. Unfortunately, taking advantage of this benefit brings with it a growing IPR risk from patent trolls, who often send bad-faith demand letters to thousands of businesses, counting on their lack of experience with the patent system to coerce them into paying settlements. By leveraging a quasi-experiment—the enactment of state anti-PAE laws in 2010–2017—I use a multi-site entry difference-in-differences relative time model and find strong evidence that a state's enactment of anti-PAE laws is critical in realizing two crowdfunding benefits: attracting VC investment into the state and diversifying the investments across industries within the state. This essay widens the focus of the crowdfunding literature from market efficiency to the democratization of the flow of VC financing, while surfacing the critical role of institutional governance of IPR risk in achieving this benefit.

Collectively, the essays in this dissertation use the lens of IPR to challenge the IS field's conventional view of a patent as a knowledge asset. Specifically, by zooming in on the patent examination process and on the deadweight loss brought by patent thickets and patent trolls, I show how an IPR perspective can contribute to our understanding of the production and value creation of digital innovation and how that understanding can inform innovation policy, which establishes the regulatory governance framework for the digital innovation ecosystem.

Essay 1

Does Feedback on Failure Affect Future Success?
Patent Examiner Feedback to Inventors of Digital Innovation

Abstract

As digital patents become increasingly dominant in innovation, scholars seek to understand the inventors' search for combinations of ideas in the knowledge landscape, characterized by patents granted. This research framework, however, does not consider the patent examination process in which inventors receive feedback with respect to innovativeness against their claims for intellectual property rights. By leveraging the history of the inventors with respect to the feedback received from examiners in the US patent examination process in 2008–2017, I provide consistent evidence that examiners' feedback can reduce the chance of rejection for applications for digital patents. Additionally, an inventor benefits more when the feedback is linked to temporally distant knowledge and to knowledge in diverse technology fields. This study enriches the production of digital innovation by revealing the entire pipeline of the patent application process and uncovers the critical role of examiners' feedback in the success of a patent application.

Keywords: Inventor failure, patent examination outcome, examiner feedback, digital innovation, intellectual property rights

Research Problem Formulation

Digital patents (e.g., for software) have been generating great interest among practitioners and scholars. IT firms are pouring enormous resources into such visions of the future as autonomous cars. Google, for instance, has racked up more patents than most automakers have in the connected and self-driving technology space.[1] With innovation becoming increasingly dependent on software (Arora et al. 2013), recent scholarly conversation indicates that digital patents not only create value for IT firms (Chung et al. 2018; Hall and MacGarvie 2010) but also are increasingly important for innovation in many other sectors (Branstetter et al. 2018; Chan et al. 2018).

Given the benefits arising from patents, scholarly conversations in economics and strategy have focused on how to generate patents by taking a knowledge production perspective, in which inventors seek to combine previously disconnected ideas across different technological domains (Fleming 2001; Fleming and Sorenson 2001, 2004). However, the highest-impact inventions are primarily grounded in conventional combinations of prior work, while featuring cross-domain combinations (Kim et al. 2016). In search of such inventions, team collaboration reduces the probability of very poor outcomes via more rigorous selection processes while increasing the probability of extremely successful outcomes as a result of greater knowledge combination opportunities (Singh and Fleming 2010).

With the prevalent use of digital technologies, IS scholars join this conversation by pointing out that digital technology is an important input to the patent generation process (Bardhan et al. 2013; Joshi et al. 2010; Kleis et al. 2012; Ravichandran et al. 2017). The focus of IS research has

[1] Retrieved May 1, 2019, from https://www.forbes.com/sites/oliverwyman/2017/05/17/google-racks-up-more-patents-than-most-automakers-on-connected-and-self-driving-cars/#5d38b2bf41ef.

been the role of digital technologies in the search for relevant knowledge and in the coordination of collaboration among inventors. For instance, data analytics technology can accelerate search by enabling existing knowledge to be identified, accessed, and combined (Saldanha et al. 2017), especially when innovation requires intensive information processing and search from diverse sources of prior technology (Wu et al. forthcoming). From the perspective of team collaboration, collaborative technologies enable inventor teams in search of knowledge combination to benefit from specialization and division of labor by reducing coordination costs (Forman et al. 2012).

Patents, however, are not merely a representation of knowledge. As property rights providing inventors with a temporary period of market power, they aim to incentivize innovation by allowing inventors to recoup the fixed costs of their research investments (Williams 2017). To gain those intellectual property rights (IPR), inventors need to submit a patent application to the patent office, and have it granted by a patent examiner with expertise in the given technical domain.

Prior findings on search for knowledge combination are limited to the knowledge landscape, characterized by the patents granted at the end of examination processes. Yet the patent examination process is hardly a one-shot decision by the examiner. Most applications (86.4%) fail on the first try (Carley et al. 2015). Additionally, the examination process can take significant time—an average of 3.2 years (Farre-Mmensa et al. 2018). At the heart of the process is the examiner's significant scrutiny of the inventor's claims. This scrutiny can involve several rounds of rejection (Williams 2017). Thus, it becomes important to understand the effect of examiners' feedback, when rejecting claims, on the outcomes of inventors' future patent applications.

This study takes an initial step to address this issue by considering the history of the inventor with respect to the feedback from patent examiners. By focusing on patent applications related to digital innovation—specifically, in communication, hardware and software, computer peripherals, information storage, and business methods—I aim to answer: *Does the examiners' feedback affects the outcome of an inventor's future patent application for digital innovation and if so, how?*

Patent Examination Process and Outcome[2]

In the United States, the patent examination process begins when an inventor submits an application to the US Patent and Trademark Office (USPTO). The application then goes through the pre-examination process to ensure that all necessary information is included. A complete application has two key sections: (a) a description of the invention that includes all citations to prior patent documents and scientific and commercial literature and (b) a list of the inventor's claims for IPR. As a part of the pre-examination, the application is assigned to a patent examiner with expertise in the invention's technical domain.

In compliance with US Code Title 35 (35 U.S.C.),[3] the examiner is required to conduct two types of evaluation of the claims:

Procedural evaluation. The examiner will make sure that the claims are directed to patent-eligible subject matter (35 U.S.C. Section 101), that the description of inventions satisfies the disclosure requirements, and that the claims clearly define the invention (35 U.S.C. Section 112).

Innovativeness evaluation. The examiner will look for prior art (i.e., patent documents or other nonpatent literature) to determine whether the invention is novel—that is, not anticipated by

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[2] Please refer to Graham et al. (2018) for a comprehensive description of the patent examination process.
[3] Retrieved May 1, 2019, from https://www.uspto.gov/web/offices/pac/mpep/consolidated_laws.pdf.

prior art (35 U.S.C. Section 102)—and nonobvious—that is, sufficiently different from what has been described in the prior art (35 U.S.C. Section 103).

Based on these evaluations, the examiner may allow all claims and the inventor can be granted a patent. However, in most cases, the examiner sends the inventor an office action that rejects one or more claims, based on her procedural and innovativeness evaluations. USPTO recommends that examiners use office action templates with standardized headings and custom form paragraphs to render documents consistent, easy to read, and legally proper. Standardized headings and form paragraphs provide legal terms and definitions relevant to the objections and/or rejections being raised (Lu et al. 2017).

Figures 1–3 provide three examples of claim rejections for different reasons. The rejection in Figure 1 is based on the procedural evaluation; claims 1–8 and 10 are not patent-eligible subject matter. The rejection in Figure 2 is based on the innovativeness evaluation; claims 1, 2, 5, 6, 8, 11, 12, and 13 lack novelty since they are anticipated by prior patent document US 2005/0169483. Similarly, in Figure 3, claims 1–19 are obvious to patent document USPN 2008/147642.

Figure 1.
Claim Rejection: Nonpatentable Subject Matter

Claim Rejections - 35 USC § 101

3. 35 U.S.C. 101 reads as follows:

> Whoever invents or discovers any new and useful process, machine, manufacture, or composition of matter, or any new and useful improvement thereof, may obtain a patent therefor, subject to the conditions and requirements of this title.

4. Claim 1-8, 10 rejected under 35 U.S.C. 101 because the claimed invention is directed to a judicial exception of an abstract idea or a non-statutory subject matter.

Figure 2.
Claim Rejection: Lack of Novelty

Claim Rejections - 35 USC § 102

2. The following is a quotation of the appropriate paragraphs of 35 U.S.C. 102 that form the basis for the rejections under this section made in this Office action:

> A person shall be entitled to a patent unless –
>
> (a)(1) the claimed invention was patented, described in a printed publication, or in public use, on sale or otherwise available to the public before the effective filing date of the claimed invention.

3. Claims 1, 2, 5, 6, 8, 11, 12 and 13 are rejected under 35 U.S.C. 102(a)(1) as being anticipated by **US 2005/0169483 (Malvar et al.)**.

Figure 3.
Claim Rejection: Obviousness

Claim Rejections - 35 USC § 103

The following is a quotation of pre-AIA 35 U.S.C. 103(a) which forms the basis for all obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or described as set forth in section 102 of this title, if the differences between the subject matter sought to be patented and the prior art are such that the subject matter as a whole would have been obvious at the time the invention was made to a person having ordinary skill in the art to which said subject matter pertains. Patentability shall not be negatived by the manner in which the invention was made.

4. Claims 1-19 rejected under pre-AIA 35 U.S.C. 103(a) as being unpatentable over Dean (USPN 20080147642, referred to as Dean) and Examiner's official notice.

Upon receiving the examiner's feedback, the inventor generally has three months to decide whether to submit a response along with a list of revised claims or just abandon the application. If the inventor chooses to continue the examination process, the examiner will evaluate the revised claims to determine whether the rejections have been overcome. If no issue remains, the inventor will be notified that the claims are allowable. Otherwise, the examiner may find that the inventor's arguments are insufficient to overcome the rejections or that her revised claims raise further issues and therefore send her another office action.

In most cases, patent examination is an iterative process with several rounds of rejection and revision. Even though the inventor can always submit a response to a rejection, she presumably chooses between "revise and resubmit" and "abandon" by considering the tradeoff between costs and benefits: If a successful revision would result in a patent too narrow to provide much economic value, the inventor would likely abandon the application.

The patent examination process provides rich indicators at different levels from a variety of perspectives with which to evaluate how an inventor performs in her application for IPR:

- Number of claims (total, procedural, innovativeness) rejected by round
- Number of claims (total, procedural, innovativeness) rejected by application
- Number of rounds in an application
- Application granted or not

An example. Amazon's Alexa is a virtual assistant, which users can activate with a wake-word such as "Alexa." Figure 4 is a patent application (13/929,540, "Detecting Self-Generated Wake Expression") related to this technology. Although Amazon submitted this application on June 27, 2013, it was not granted until August 29, 2017. Table 1 tabulates the complete four-round examination process.

Figure 4.
Amazon's Patent Application: "Detecting Self-Generated Wake Expression"

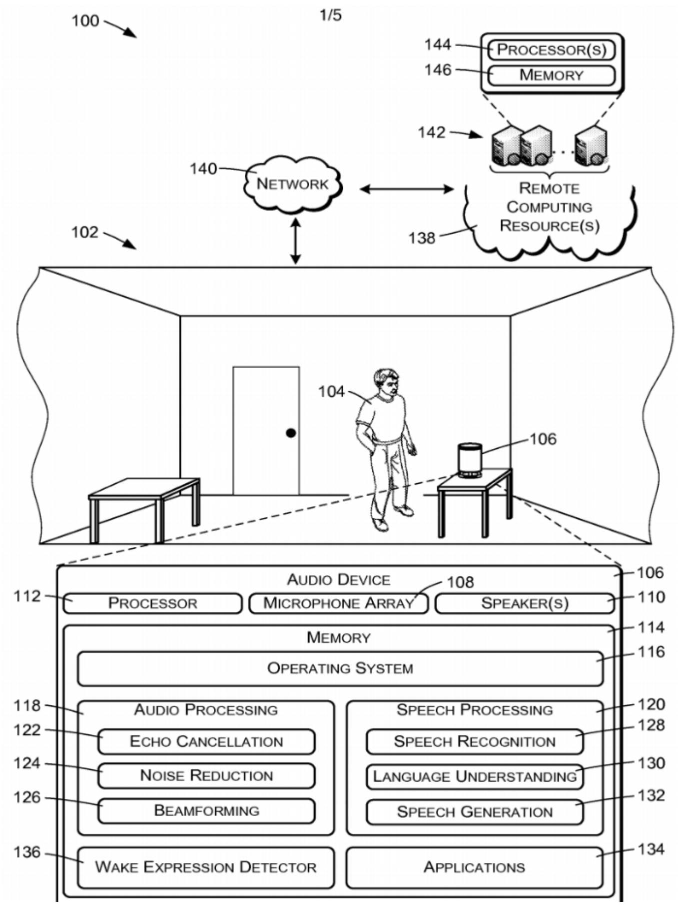


Table 1.
Examination Process of Patent Application 13/929,540

	Round 1	Round 2	Round 3	Round 4
Inventor submission date	June 2013	March 2016	August 2016	December 2016
Examiner office action date	December 2015	May 2016	September 2016	Patent granted in August 2017
# claim rejections (total)	20	19	9	-
# claim rejections (procedural evaluation)	20	19	9	-
# claim rejections (innovativeness evaluation)	20	19	9	-
# references in innovativeness rejection	2	3	3	-

Inventor Learning from Examiner Feedback

Literature using archival data largely finds evidence of learning from failure in different scenarios at different level of analysis. Riedl and Seidel (2018), studying T-shirt design contests, find that participants can improve their performance by observing others' failures. Madsen and Desai (2010) find evidence that a future satellite launch is more likely to succeed with a greater number of failed launches. Both Audia and Goncalo (2007) and Baum and Dahlin (2007) provide empirical evidence that cumulative past success drives organizations' local search for minor performance improvements and that, as the number of failures increases, organizations tend to search beyond their knowledge boundaries for new ideas.

In rejecting an inventor's claim for lack of innovativeness, the examiner cites the relevant prior art. Such feedback, however, is not only useful for administrative purposes. USPTO patent examiners are required to have a science or engineering background and expertise in a specific technology field (Righi and Simcoe 2019); they tend to have this role at USPTO for an average of 10 years.[4] By learning from such expert feedback, the inventor can ease the "burden of knowledge" and enrich her own knowledge landscape, which generates more opportunities for her to search for successful combination of previously disconnected ideas (Jones 2009). She also becomes better positioned to survive future patent examinations.

The influence of examiners' feedback is subject to the temporal and technological scope of that feedback. While feedback pointing to recent and domain-concentrated knowledge can enrich the inventor's knowledge landscape, it only facilitates local search in the smooth, correlated knowledge landscape in which the inventor moves across adjacent positions, which results in

[4] Retrieved May 1, 2019, from https://www.uspto.gov/dashboards/patents/main.dashxml.

incremental inventions (Fleming 2001). In contrast, feedback linked to temporally distant knowledge and to knowledge in diverse technology fields prevents the inventor from being trapped on a local peak in the knowledge landscape and helps her move across jumbled and uncorrelated positions, results in novel knowledge combinations and inventions (Fleming 2001).

Therefore, I expect that *(a) examiners' feedback can help the inventor survive future patent applications for digital innovation and (b) she is more likely to generate successful patent applications when the feedback is linked to temporally distant knowledge and to knowledge in diverse technology fields*.

Research Design

Data

I conduct the analysis at two levels: inventor-application-round and inventor-application. I construct the dataset regarding digital innovation from publicly available datasets on the USPTO Chief Economist Office website.

Office action data. I use the recently released USPTO Office Action Dataset for Patents,[5] which uses machine learning to systematically extract office action information issued in 2008–2017 from image files for publicly available utility patent applications via the USPTO Public Patent Application Information Retrieval system. Specifically, this dataset enables me to extract which claim is rejected for what reason—procedural or innovativeness. It also includes the relevant prior art which the examiner uses to reject an inventor's claim for lack of innovativeness.

[5] Please refer to Lu et al. (2017) for a comprehensive description of this dataset.

Patent examination data. To extract the information in each office action, I use the USPTO Patent Examination Research Dataset, which provides a wealth of microlevel administrative data on US patents, patent applications, and their examination histories.

Patent application data. I use the USPTO PatentsView platform—a new database that longitudinally links inventors and their organizations, locations, and overall patenting activity—to collect all granted and nongranted utility patent information (e.g., application date, grant date, inventor name, inventor gender, inventor affiliation, lawyer information, and patent classification). Based on the NBER patent classification (Hall 2001 and PatentsView), I select patent applications that fall into the categories of digital innovation: communication, hardware and software, computer peripherals, information storage, and business methods (such as fintech and machine learning algorithms). I then link the corresponding office action information to these patents. In addition, for each patent cited in the office action with respect to innovativeness evaluation, I identify relevant information from PatentsView.

After merging all data with the office actions regarding digital innovation in 2008–2017, I obtain two levels of samples. For the inventor-application-round–level analysis, I obtain 59,380 observations from 9,888 inventors who have gone through at least two rounds in the patent examination process and whose first application is included in the sample. For the inventor-application–level analysis, I extract 25, 203 observations from 7,451 inventors who have submitted at least two applications and whose first application is contained in the sample. Tables 2 and 3 provide descriptive information of the sample at these two levels.

Methods

Baseline model specification. To investigate how examiners' feedback regarding claim innovativeness affects an inventor's future patent examination outcomes, I construct two baseline models: one at the inventor-application-round level and one at the inventor-application level.

$$\begin{aligned}Claim\_Rej\_rnd_{it} = \alpha + \; & \beta_1 \times LogInno\_Rej\_rnd_{it-1} \\ & + \beta_2 \times LogTempScope\_rnd_{it-1} + \beta_3 \times LogTechScope\_rnd_{it-1} \\ & + \beta_4 \times LogTempScope\_rnd_{it-1} \times LogInno\_Rej\_rnd_{it-1} \\ & + \beta_5 \times LogTechScope\_rnd_{it-1} \times LogInno\_Rej\_rnd_{it-1} \\ & + Controls \; + \; \varepsilon_{it}, \qquad \text{… Equation (1)}\end{aligned}$$

where *i* denotes inventor and *t* denotes the time when the office action for the focal application-round is sent from the examiner. All variables are at the inventor-application-round level. Table 2 provides definitions of the variables. As $Claim\_Rej\_rnd_{it}$ is a count variable, I use negative binomial and Poisson model specifications.

$$\begin{aligned}D\_Variable_{it} = \alpha + \; & \beta_1 \times LogInno\_Rej\_app_{it-1} \\ & + \beta_2 \times LogTempScope\_app_{it-1} + \beta_3 \times LogTechScope\_app_{it-1} \\ & + \beta_4 \times LogTempScope\_app_{it-1} \times LogInno\_Rej\_app_{it-1} \\ & + \beta_5 \times LogTechScope\_app_{it-1} \times LogInno\_Rej\_app_{it-1} \\ & + Controls \; + \; \varepsilon_{it} \;, \qquad \text{… Equation (2)}\end{aligned}$$

where *i* denotes inventor and *t* denote the time when the last office action for the focal application was sent. All variables are on the inventor-application level. Dependent variables are $Claim\_Rej\_app_{it}$, $Round\_app_{it}$, and $Grant\_app_{it}$. Table 3 provides definitions of the variables. I use a Poisson model specification when the dependent variable is $Claim\_Rej\_app_{it}$ or $Round\_app_{it}$ and a Probit model specification when the dependent variable is $Grant\_app_{it}$.

Table 2.
Level of Analysis: Inventor-Application-Round
Definitions and Descriptive Statistics of Variables

Variable	Definition	Mean	Std. dev.
Claim_Rej_rnd	Number of claims rejected by the examiner in the focal inventor-application-round at time t	23.53	17.01
Inno_Rej_rnd	Inventor's number of innovativeness claim rejections at time t-1	377.33	642.91
TempScope_rnd	For all patents cited by examiners related to innovativeness in the office action for the focal inventor before t, calculate the average difference (in years) between the filing date of the cited patent and the mail date of the office action in which the focal patent is cited	7.96	2.52
TechScope_rnd	For all patents cited by examiners related to innovativeness in the office action for the focal inventor before t, calculate the Herfindahl index based on each cited patent's NBER subtechnology class. 1 represents the most concentrated case and 0 represents the most diverse case.	0.83	0.14
Proce_Rej_rnd	Inventor's number of procedural claim rejections at time t-1	158.94	287.18
Inventor_Patent	Inventor's number of granted patents at time t-1	9.00	17.88
Examiner_Patent	Examiner's number of granted patents at time t-1	230.25	358.25
Lawyer_Patent	Lawyer's number of granted patents at time t-1. If there is more than 1 lawyer in the focal patent application, I average their numbers of patents.	2819.6	6301.14
Inventor_Affiliation	1 if the focal inventor is affiliated with an organization, 0 otherwise	0.99	0.02
Inventor_Male	1 if the focal inventor is male, 0 otherwise	0.86	0.35
Invention_Team	1 if the focal inventor has at least one collaborator, 0 otherwise	0.51	0.50

Table 3.
Level of Analysis: Inventor-Application
Definitions and Descriptive Statistics of Variables

Variable	Definition	Mean	Std. dev.
Claim_Rej_app	Number of claims rejected by the examiner in the focal inventor-application at time t	42.45	39.11
Round_app	Number of rounds the focal inventor has gone through for the focal inventor-application at time t	3.22	1.45
Grant_app	1 if the focal patent has been granted at time t, 0 otherwise	0.77	0.42
Inno_Rej_app	Inventor's number of innovativeness claim rejections at time t-1	229.24	395.55
TempScope_app	For all patents cited by examiners related to innovativeness in the office action for the focal inventor before t, calculate the average difference (in years) between the filing date of the cited patent and the mail date of the office action in which the focal patent is cited	7.86	2.80
TechScope_app	For all patents cited by examiners related to innovativeness in the office action for the focal inventor before t, calculate the Herfindahl index based on each cited patent's NBER subtechnology class. 1 represents the most concentrated case and 0 represents the most diverse case.	0.82	0.17
Proce_Rej_app	Inventor's number of procedural claim rejections at time t-1	122.67	219.96
Inventor_Patent	Inventor's number of granted patents at time t-1	9.09	16.74
Examiner_Patent	Examiner's number of granted patents at time t-1	309.92	424.16
Lawyer_Patent	Lawyer's number of granted patents at time t-1. If there is more than 1 lawyer in the focal patent application, I average their numbers of patents.	3082.26	6456.43
Inventor_Affiliation	1 if the focal inventor is affiliated with an organization, 0 otherwise	0.99	0.02
Inventor_Male	1 if the focal inventor is male, 0 otherwise	0.87	0.34
Invention_Team	1 if the focal inventor has at least one collaborator, 0 otherwise	0.55	0.50

Controls. As I am interested in the impact of innovativeness feedback, I control for procedural rejections. For inventors, I include their gender and affiliation as control variables. I also control for the characteristics of other stakeholders (such as collaborators, examiners, and lawyers). To rule out the heterogeneity between rounds in a focal patent application, I control for round number. I also include technology fixed effects based on digital innovation categories (communication, hardware and software, computer peripherals, information storage, and business methods) to tease out the heterogeneity among these technologies. I include year fixed effects to control for time-variant factors affecting all patent applications.

Instrument variable. A potential problem of the baseline models is that they are subject to omitted variables, such as the inventor's ability. Since that inventor characteristic is negatively related to both *Claim_Rej_rnd* and *LogInno_Rej_rnd* in Equation (1), I would expect to see a positive relationship between the two variables (i.e., β_1>0). To address this concern, I leverage the focal inventor's previous collaborators who (a) have also worked with other inventors and (b) are not involved in the focal patent application. Based on innovativeness claim rejection information for these collaborators, I construct instrument variables for *LogInno_Rej_rnd*, *LogTempScope_rnd*, *LogTechScope_rnd*, *LogInno_Rej_app*, *LogTempScope_app*, and *LogTechScope_app*. The intuition is that these instrument variables are related to my variables of interest for the focal inventor due to past collaboration. But they are less likely to affect the outcome of the focal application as these collaborators are not involved in it and because their work with other inventors accounts for an average of 70% of their past patent applications (see Table 4 for details).

Table 4.
Validity of Using Collaborators' Claim Rejection Information as Instruments

Statistics	Round	Application
# inventors in the sample	9,888	7,451
# collaborators for the focal inventors	25,663	22,238
For each collaborator:		
Average # patent applications	10.6	10.8
Average # patent applications with the focal inventor	3.1	3.2
Average # patent applications with other inventors	7.5	7.6

Results

Round level. I first explore whether examiners' feedback can help the inventor survive future patent applications for digital innovation. The negative binomial and Poisson results (Table 5) indicate that the relationship between *Claim_Rej_rnd* and *LogInno_Rej_rnd* is positive. Because, as I discussed in the methods section, this could be due to endogeneity, I implement instrument variables in Equation (1). This time, I find that the cumulative innovativeness feedback an inventor received from examiners is negatively associated (-0.966, z=-4.93, p<0.001) with her number of claim rejections in the next round of patent examination. In addition, such benefits are subject to the temporal (-0.237, z=-4.96, p<0.001) and technological (1.016, z=4.84, p<0.001) scope of the feedback. As expected, the inventor benefits more when the feedback is linked to temporally distant knowledge and to knowledge across diverse technology fields.

Application level. I use similar instrument variables to conduct application-level analysis based on Equation (2). Consistent with the results in the round-level analysis, the cumulative innovativeness feedback an inventor received from examiners is negatively associated (-1.046, z=-2.49, p<0.05 in Table 6) with her number of claim rejections in the next round of patent application. Again, this benefit is contingent on the temporal (-0.379, z=-3.45, p<0.001) and technological (1.139, z=2.74, p<0.01) scope of the feedback. In addition to number of claims rejected in the next patent application, I am interested in whether the inventor goes through fewer rounds and is more likely to have her patent granted when she learns from the innovativeness feedback. The results reported in Table 6 support this point.

To sum up, the analysis provides consistent evidence that innovativeness feedback from patent examiners helps an inventor survive future patent applications. She benefits more from feedback linked to temporally distant knowledge and to knowledge across diverse technology fields.

Table 5.
Inventor-Application-Round Analysis of Effect of Examiner's Feedback on the Outcome of an Inventor's Next Patent Application for Digital Innovation

	DV=*Claim_Rej_rnd*		
Variable	**Negative binomial**	**Poisson**	**IV Poisson**
LogInno_Rej_rnd	0.0590*	0.0464***	-0.966***
	(2.43)	(5.14)	(-4.93)
LogTempScope_rnd	0.139***	0.129***	1.287***
	(4.02)	(9.82)	(5.10)
LogTechScope_rnd	-0.412***	-0.500***	-5.512***
	(-3.56)	(-11.37)	(-4.58)
LogTempScope_rnd * LogInno_Rej_rnd	-0.00845	-0.00744**	-0.237***
	(-1.14)	(-2.70)	(-4.96)
LogTechScope_rnd * LogInno_Rej_rnd	0.0415+	0.0614***	1.016***
	(1.67)	(6.56)	(4.84)
LogProce_Rej_rnd	0.0379***	0.0386***	0.0877***
	(13.50)	(35.83)	(6.55)
LogInventor_Patent	-0.0886***	-0.0872***	-0.156***
	(-26.10)	(-71.77)	(-25.04)
LogExaminer_Patent	0.0317***	0.0323***	0.0520***
	(19.86)	(55.18)	(21.58)
LogLawyer_Patent	0.000332	0.000586+	0.00664***
	(0.37)	(1.77)	(5.86)
Inventor_Affiliation	0.00260	0.00633	-0.227
	(0.02)	(0.13)	(-1.54)
Inventor_Male	0.0300***	0.0386***	0.0473***
	(4.49)	(15.72)	(5.94)
Invention_Team	0.0467***	0.0427***	0.0420***
	(9.52)	(23.91)	(6.92)
Class_Communication		Baseline	
Class_Hardware&Software	0.0169**	0.00991***	0.0244**
	(2.68)	(4.33)	(2.94)
Class_Peripherials	-0.127***	-0.132***	-0.0952***
	(-15.40)	(-41.51)	(-7.89)
Class_Storage	0.0116	0.000679	0.0134
	(1.39)	(0.22)	(1.38)
Class_Business_Method	0.136***	0.129***	0.110***
	(18.11)	(48.93)	(10.40)
Year FE		Included	
Intercept	4.006***	4.053***	9.166***
	(20.60)	(59.27)	(8.21)
N	59380	59380	59380

Note: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001

Table 6.
Inventor-Application Analysis of Effect of Examiner's Feedback on the Outcome of an Inventor's Next Patent Application for Digital Innovation

Variable	DV=*Claim_Rej_app* IV Poisson	DV=*Round_app* IV Poisson	DV=*Grant_app* IV Probit
LogInno_Rej_rnd	-1.046*	-0.330+	1.693+
	(-2.49)	(-1.70)	(1.88)
LogTempScope_rnd	1.982***	0.811***	-2.412*
	(3.60)	(3.65)	(-2.55)
LogTechScope_rnd	-6.981**	-1.448	2.686
	(-3.12)	(-1.39)	(0.53)
LogTempScope_rnd * LogInno_Rej_rnd	-0.379***	-0.186***	0.714***
	(-3.45)	(-3.97)	(3.52)
LogTechScope_rnd * LogInno_Rej_rnd	1.139**	0.194	-0.832
	(2.74)	(0.96)	(-0.83)
LogProce_Rej_rnd	0.0712*	0.00958	-0.144*
	(2.32)	(0.69)	(-2.30)
LogInventor_Patent	-0.351***	-0.133***	0.487***
	(-21.51)	(-17.56)	(12.17)
LogExaminer_Patent	0.103***	0.0168***	0.0758***
	(16.32)	(6.25)	(6.44)
LogLawyer_Patent	0.0176***	0.00812***	-0.00889
	(6.51)	(6.76)	(-1.61)
Inventor_Affiliation	-0.571+	-0.273*	-0.206
	(-1.68)	(-1.98)	(-0.41)
Inventor_Male	0.0629***	-0.00314	0.157***
	(3.37)	(-0.38)	(4.58)
Invention_Team	0.00534	-0.0663***	1.038***
	(0.41)	(-11.51)	(37.25)
Class_Communication		Baseline	
Class_Hardware&Software	0.0391*	0.0293***	-0.184***
	(2.36)	(3.70)	(-5.18)
Class_Peripherials	0.00495	0.0762***	-0.270***
	(0.22)	(7.45)	(-6.46)
Class_Storage	0.129***	0.0968***	-0.0480
	(6.25)	(10.26)	(-1.13)
Class_Business_Method	0.187***	0.127***	-0.565***
	(8.78)	(12.70)	(-12.63)
Year FE		Included	
Intercept	10.69***	3.344***	-7.494+
	(4.63)	(3.31)	(-1.67)
N	25203	25203	25129

Note: +p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Discussion

Conclusion. This study peers into the black box of digital patent examination by identifying the influence on an inventor's future patenting outcomes of examiners' feedback pertaining to why the claims of her past applications have been rejected. It provides consistent evidence that such feedback reduces the number of claims rejected, speeds up the examination process by reducing the number of examination rounds, and increases the probability of a patent being granted. Moreover, these benefits are subject to the temporal and technological scope of the feedback; with the amount of feedback increasing, an inventor benefits more from feedback linked to temporally distant knowledge and to knowledge across diverse technology fields.

Contribution. This study contributes to the emerging literature on the production of digital innovation. It extends our understanding by integrating (a) the role of feedback from examiners to inventors on the innovativeness of their digital innovations and (b) the implications of that effect for the inventor's digital innovation production. By incorporating the role of examiner feedback, this study extends the current IS literature, which has primarily focused on the role of digital technologies for knowledge search and for coordination. Specifically, the current literature provides evidence on how inventors can leverage their knowledge base to search for knowledge combination and how digital technology can help (e.g., Fleming 2001; Wu et al. forthcoming). This study, in contrast, introduces a key stakeholder—the patent examiner—into the inventor's digital innovation production process. It specifically surfaces two key aspects of examiners' feedback—temporal and technological—which help clarify how the inventor learns from the feedback. The results suggest that examiners' feedback extending the temporal scope of knowledge considered by inventors is useful as it informs them on how to integrate temporally distant knowledge in formulating their claims for innovativeness and for knowledge combination. Similarly, feedback that extends the inventors' knowledge scope to other technological categories is useful as it informs them on how to combine knowledge across domains and develop innovative claims which are more likely to be granted in the patenting process.

This study contributes to the body of work on (a) exploitation of established competencies through incremental adjustments and (b) exploration of new competencies and knowledge through radical innovation. The organization science and IS literatures have examined how exploitation tendencies in different domains can be countered through mechanisms that promote exploration (e.g., Durcikova et al. 2011; Im and Rai 2008; Levinthal and March 1993; March 1991). I contribute to this discourse by integrating the role of an expert (the examiner) in challenging inventors' myopia by orienting them toward knowledge that is more temporally distant and technological diverse. Through such reorientation of search, examiners can challenge the inventors' exploitative tendencies to search for solutions in proximate and familiar knowledge domains.

Past empirical work using patents to investigate digital innovation has relied on patents granted at the end of the examination process (e.g., Kleis et al. 2012). I approach the digital innovation process at a granular level by focusing on intermediate rounds and assessments at the level of specific claims, allowing me to examine the role of examiner feedback at different levels of analysis—inventor-application-round and inventor-application—and using different outcome measures. This research design enables me to triangulate my findings across levels of analysis and measures pertaining to inventors' production of digital innovation.

In sum, the knowledge landscape an inventor searches for knowledge combination can be significantly influenced by examiners' feedback. This study provides consistent evidence by revealing the entire pipeline of the patent application process and characterizing examiners' feedback as expanding the knowledge landscape in which inventors search for knowledge combination.

This study informs a debate among scholars regarding the expertise of patent examiners in digital patents (e.g., Burk and Lemley 2003). As documented, inventors can leverage feedback from examiners to succeed in their future claims for IPR, especially when the feedback is related to distant knowledge and to knowledge across technology areas. This study also provides more granular evidence on whether citations added by examiners reflect the knowledge available to or used by inventors (e.g., Alcacer et al. 2009). While inventors may not use the knowledge embedded in the feedback (i.e., citations) for the focal invention, it could enrich the knowledge landscape in which they search for knowledge combination in the future. Thus, this study suggests that it is necessary to adopt a temporal perspective to differentiate the value of examiners' citations.

Limitations and future research. My results indicate that inventors benefit from examiners' feedback for their future applications, but do not provide empirical evidence of the underlying mechanism. Therefore, certain open questions deserve further exploration. For instance, because an attorney handles the inventor's communication with the examiner, it is crucial to understand (a) whether the inventor actually reads the examiner's feedback and, if so, to what extent the knowledge flows to the inventor rather than to the attorney, and (b) whether the feedback changes the inventor's behavior of generating novel knowledge combination. An alternative explanation is that inventors are already aware of the prior art cited by the examiner, but do not include it in the application, hoping to gain a broader claim scope. In this case, the role of the examiner's feedback is to restrict such gaming. Future research can provide more nuanced evidence of whether and how examiners' feedback enables inventors to generate novel inventions.

During past decades, reliance on teamwork has increased, fundamentally shifting the innovation process (Fortunator et al. 2018; Wu et al. 2019; Wuchty et al. 2007). In this study, however, I focus only on the individual inventor while controlling for teamwork. An interesting finding is that teamwork does not seem to be helpful in the survival of the patent application through the examination process. This is inconsistent with the past evidence that collaboration can filter out bad ideas and make brilliant ideas stand out (Singh and Fleming 2010). Such evidence, however, is based only on the inventor's knowledge base without considering feedback from examiners. Future research can address this puzzle by (a) characterizing an inventor's expertise based on her own knowledge base and on the feedback from examiners and (b) exploring how collaborators interact—based on the expertise from these two sources—in search of knowledge combinations.

While differences across the specific types of digital patent (communication, hardware and software, computer peripherals, information storage, and business methods) is not the focus of this study, the fixed-effect results indicate that patents involving hardware/software and business models are less likely to survive the patent examination process than patents in the other three categories. This raises an intriguing question for both scholars and policy makers: Is the difference due to too many incremental patent applications saturating hardware/software and business methods or to examiners' lack of expertise in these two categories? Future research can consider both the innovativeness of inventors' claims and the examiners' capabilities to explore the underlying mechanism that leads to the difference.

Essay 2

Innovating in the IT Industry:
Mandatory Patent Disclosure and the Formation of Patent Thickets

Abstract

This study aims to understand of the formation of patent thickets in the IT industry. Specifically, what is the underlying mechanism that establishes the intellectual property rights (IPR) overlap among IT firms that may restrict their commercialization of their own inventions? With the enactment of the American Inventor's Protection Act (AIPA) in 2000, a firm is required to publicly disclose a patent application 18 months after the filing day. This study outlines two competing predictions on how such pre-grant patent disclosure will affect an IT firm's IPR overlap with its competitors: (a) a constraining influence due to patent examiners' evaluation taking the pre-grant disclosures into account while assessing competitors' patent claims and (b) knowledge spillover when technical information and market signals are revealed to competitors. To evaluate these competing explanations, I exploit the natural experiment of the enactment of AIPA. I find that the knowledge spillover effect dominates, especially when the technological and market values of the disclosure are high. Moreover, the knowledge spillover effect is more pronounced when the focal IT firm and its competitors are close in technology space and product market. This study reveals the innovation interdependency among IT firms in terms of IPR and uncovers the underlying mechanism by which it evolves. Thus, it provides more nuanced evidence of the dynamics of innovation in the IT industry.

Keywords: Patent disclosure, patent thicket, intellectual property rights overlap, IT industry, innovation, commercialization

Research Problem Formulation

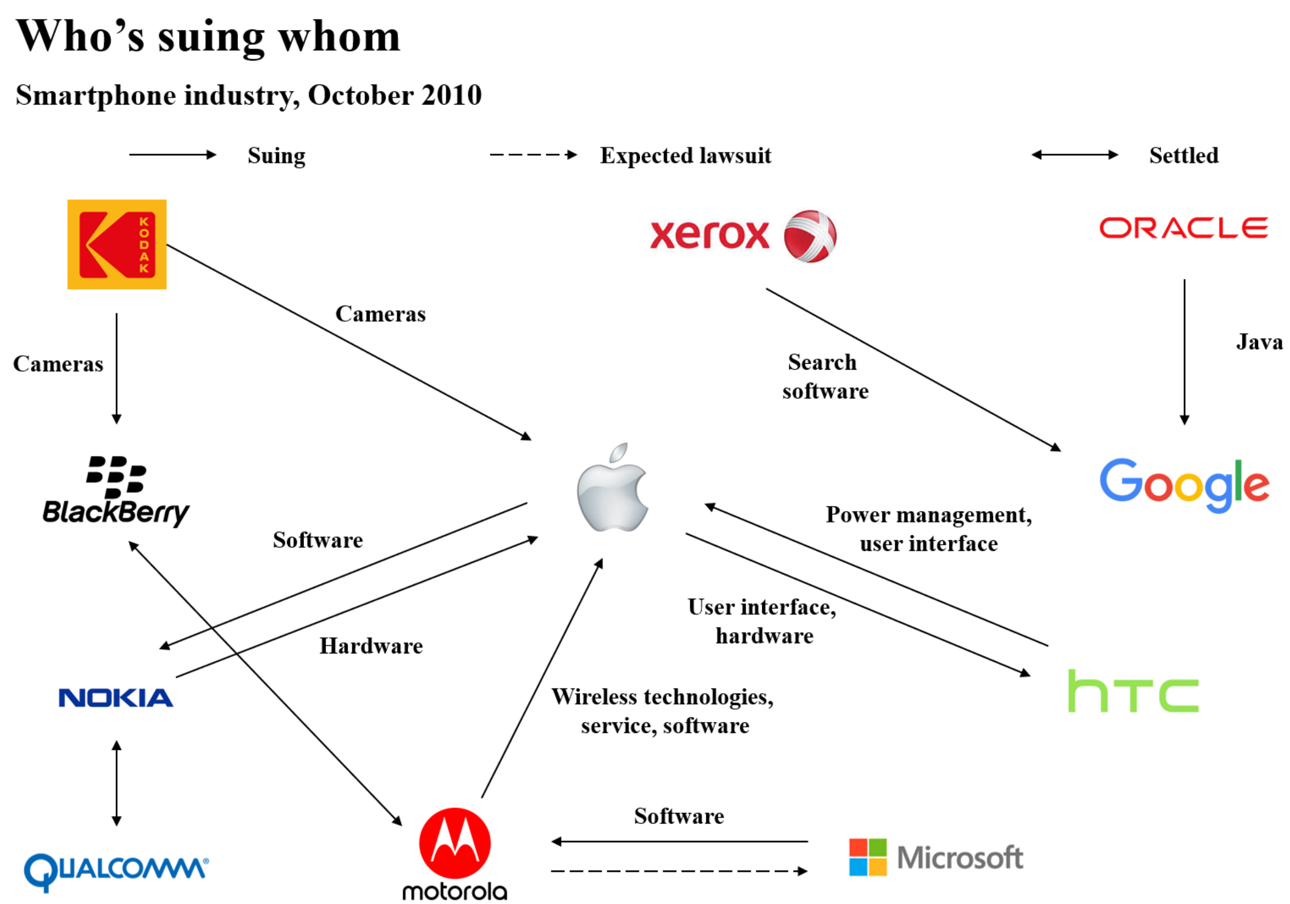
In recent years, there has been an outbreak of wars over digital patents. In the smartphone industry, for example, major vendors haven been enforcing patents against competitors (see Figure 1) since 2009.[6] On May 24, 2018, a jury awarded Apple $539 million for damages, seven years after the start of its patent battle with Samsung over key components of their smartphones.[7] With IT firms racing to assemble patent portfolios and develop digital products and services in new technology fields such as autonomous cars, augmented reality, smart devices, blockchain, and artificial intelligence, we can expect even bigger patent wars in the next few decades.

The emergence of such patent wars is a result of technology convergence in a single digital product or service which involves a myriad of hardware and software patents (Graham and Vishnubhakat 2013). For example, "the number of patents in a smartphone is so huge that nobody has ever been able to count," says Florian Mueller, founder of the FOSS Patents blog and an intellectual property activist. "Besides, you'd have to look not only at smartphone patents but also hundreds of thousands or millions of software patents."[8] Therefore, commercializing a smartphone without rights to use all relevant patents can lead to infringement claims.

The problem of patent thickets has inspired a growing concern among scholars and policy makers that patent rights are themselves becoming an impediment—rather than an incentive—to innovation (Federal Trade Commission 2012; Galasso and Schankerman 2015). For instance, patent thickets can hold up innovations (Bessen and Meurer 2013), increase the complexity of license negotiations (Wen and Forman 2016), increase litigation (Bessen and Meurer 2013), and

[6] Retrieved May 1, 2019, from https://www.economist.com/business/2010/10/21/the-great-patent-battle.
[7] Retrieved May 1, 2019, from https://www.bloomberg.com/news/articles/2018-05-24/apple-wins-539-million-from-samsung-in-damages-retrial.
[8] Retrieved May 1, 2019, from https://www.wired.co.uk/article/apple-samsung-iphone-patents.

Figure 1
Patent Wars in the Smartphone Industry



create incentives to add more—but often weaker—patents to the patent system (Allison et al. 2015). The increased transaction costs associated with patent thickets reduce profits from the commercialization of innovation, thus working as a barrier to entry into technology sectors (Hall et al. 2017; Cockburn and MacGarvie 2011; Wen et al. 2015), and ultimately reduce innovation incentive (Hall et al. 2017) and business dynamism (Akcigit et al. 2018).

To mitigate the patent thickets problem, firms rely on multi-firm institutional arrangements such as patent pools (e.g., Via LTE[9]), standard-setting organizations (e.g., 3rd Generation Partnership Project[10]), and cross-licensing, which lowers the transaction costs of identifying and negotiating patent licensing agreements for related technologies. However, such cooperative mechanisms have limitations. For example, while patent pools are predicted to address patent thickets (Lerner and Tirole 2004), they can create another problem by shifting innovation toward improving an inferior substitute for the pool (Lampe and Moser 2013). Besides, the sustainability of these cooperative mechanisms is questionable. IT-intensive industries evolve rapidly and are often dominated by a few players (Bessen 2017); cooperation is therefore likely to break down as dominant players convert their patent portfolios into weapons to eliminate competition (Shaver 2012).

The current scholarly conversation on patent thickets mainly focuses on their adverse effects on innovation and on potential solutions. However, we still have limited understanding of the micro-foundation with regard to the *formation* of patent thickets in the IT industry. Specifically, what underlying mechanism establishes the IPR overlap that may restrict a firm's commercialization of its own invention? With the enactment of the American Inventor's

[9] Retrieved May 1, 2019, from http://www.via-corp.com/us/en/licensing/lte/overview.html.
[10] Retrieved May 1, 2019, from https://www.3gpp.org.

Protection Act (AIPA) in 2000, a firm is required to publicly disclose a patent application 18 months after the filing day. On the one hand, such disclosure can generate visible prior art in the patent examination process that is likely to compromise the novelty of patent applications from competitors, pre-empting them from holding patents in the focal firm's fields of interest and thus reducing IPR overlap (Guellec et al. 2012). On the other hand, knowledge spillover due to the disclosure can stimulate competitors to innovate in the same domain (Bloom et al. 2013). One can then expect more IPR overlap.

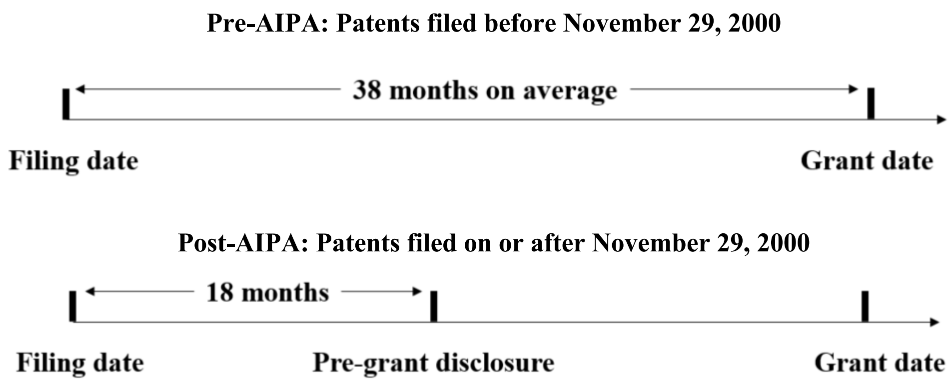
I aim to resolve these competing predictions in the context of IT industry. More formally, I ask: *Does the disclosure of patent information by an IT firm affect the IPR overlap with peers that may restrict its commercialization of its own inventions and, if so, how?* I answer by leveraging the natural experiment arising from the enactment of AIPA, which I discuss next.

The American Inventor's Protection Act

To facilitate technology diffusion, reduce duplicative research, and promote innovation, the American Inventor's Protection Act of 1999 came into effect on November 29, 2000, requiring public disclosure of a patent application 18 months after the filing day, even if the patent has not yet been granted.[11] Patent applicants had previously been allowed to keep their applications secret until the patent was granted, which took on average 38 months (Graham and Hegde 2015), so this law was a significant advance in the disclosure of firms' innovative activities, as summarized in Figure 2.

[11] All US patent applications with foreign parallel applications (filed in the EU or Japan, for example) must be published 18 months after the first application, whereas inventors filing patents only in the US can opt out of the 18-month disclosure requirement by submitting a nonpublication request to the USPTO. This request can be withdrawn during the patent examination process, but a disclosure decision cannot be. According to Graham and Hegde (2015), for 10% of US patents in the computer and communication fields filed between November 29, 2000 and the end of 2005, the applicants opted out.

Figure 2.
Summary of Disclosure Change Due to AIPA



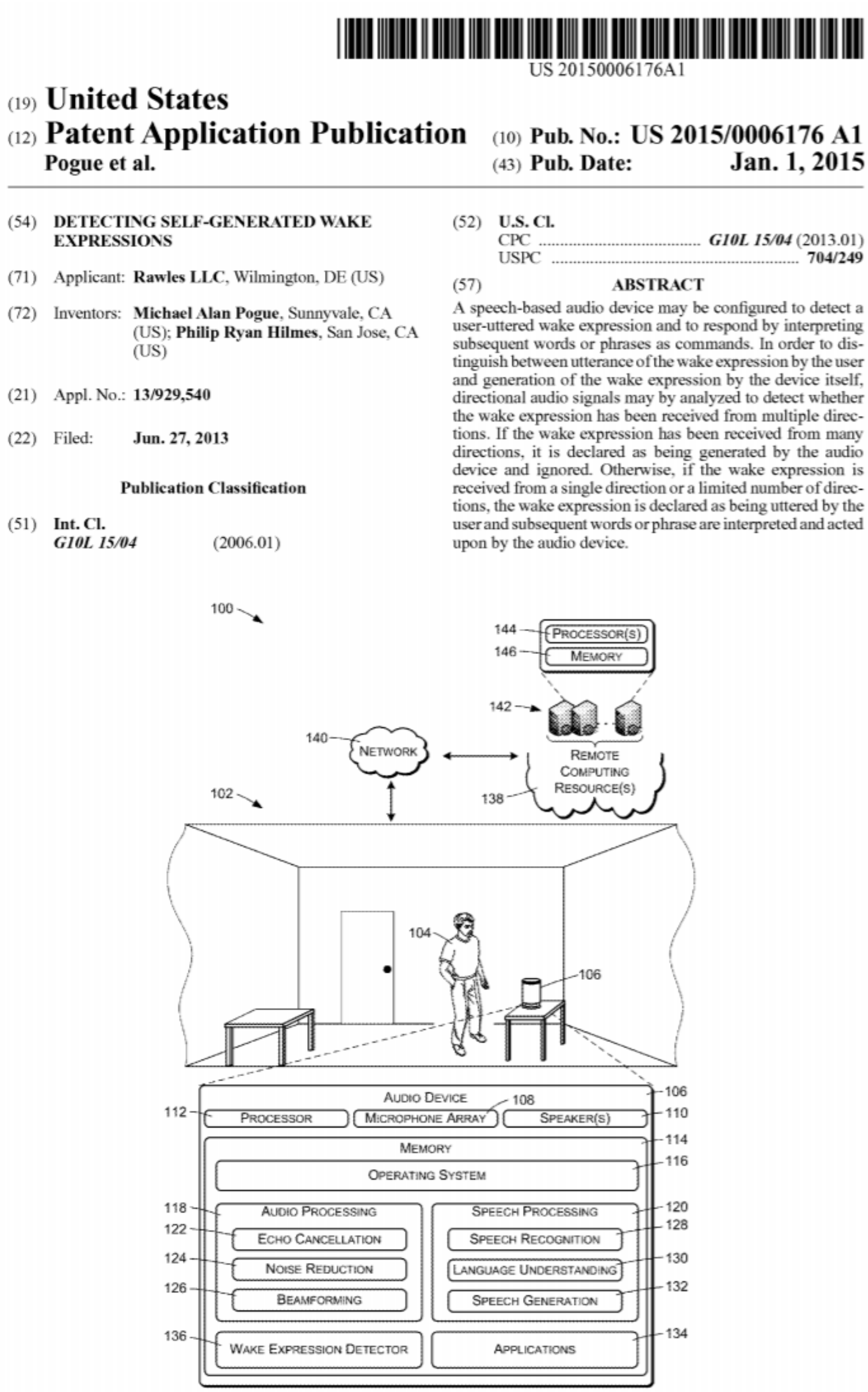
The published patent applications are posted in the USPTO Patent Application Full-Text and Image Database[12] every Thursday. The entire patent document is available to the public through this database, including a detailed description of the invention, the technological claims that define its scope, and technical drawings that illustrate its mechanisms. Figure 3 provides an example of a pre-grant disclosure of an invention (Pub. No. US2015/0006176) by Amazon that allows users to activate Alexa using a wake-word such as "Alexa."

Patent Disclosure and IPR Overlap

I outline two competing explanations of how patent disclosure will affect the IPR overlap: (a) a constraining influence due to patent examiners' evaluations that take the focal firm's pre-grant disclosures into account while assessing competitors' patent claims and (b) knowledge spillover due to technical information and market signals being revealed to competitors. I identify two sources of heterogeneity affecting the spillover and consequently the IPR overlap: (a) the value (technological and market) of the focal firm's pre-disclosure and (b) closeness (technological and market) between the focal IT firm and its competitors.

[12] http://appft.uspto.gov/netahtml/PTO/search-bool.html.

Figure 3.
Amazon's Patent Application: "Detecting Self-Generated Wake Expression"[13]



US 20150006176A1

(19) **United States**
(12) **Patent Application Publication** (10) **Pub. No.: US 2015/0006176 A1**
Pogue et al. (43) **Pub. Date: Jan. 1, 2015**

(54) **DETECTING SELF-GENERATED WAKE EXPRESSIONS**

(71) Applicant: **Rawles LLC**, Wilmington, DE (US)

(72) Inventors: **Michael Alan Pogue**, Sunnyvale, CA (US); **Philip Ryan Hilmes**, San Jose, CA (US)

(21) Appl. No.: **13/929,540**

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Publication Classification

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G10L 15/04 (2006.01)

(52) **U.S. Cl.**
CPC ***G10L 15/04*** (2013.01)
USPC **704/249**

(57) **ABSTRACT**

A speech-based audio device may be configured to detect a user-uttered wake expression and to respond by interpreting subsequent words or phrases as commands. In order to distinguish between utterance of the wake expression by the user and generation of the wake expression by the device itself, directional audio signals may by analyzed to detect whether the wake expression has been received from multiple directions. If the wake expression has been received from many directions, it is declared as being generated by the audio device and ignored. Otherwise, if the wake expression is received from a single direction or a limited number of directions, the wake expression is declared as being uttered by the user and subsequent words or phrase are interpreted and acted upon by the audio device.

[13] Retrieved on May 1, 2019, from https://patents.google.com/patent/US20150006176A1/en?oq=us20150006176.

During the patent examination process, an examiner will look for prior art to determine whether the application's claims are novel and nonobvious. The pre-grant disclosure increases the search space for an examiner to identify prior art and use it as the basis to reject claims in competitors' applications. Given such feedback, the competitors have to decide whether to revise the scope of their claims or abandon the application. If a revision accommodating the examiner's feedback would result in a patent that, even if granted, would be too narrow to provide much economic value, the competitors would likely abandon the application. Competitors will thus be pre-empted from holding patents in the fields in which the focal firm has provided pre-grant disclosure, which will reduce IPR overlap.

The disclosed patent information is valuable not only in helping the patent examiner evaluate claims in competitors' applications, but also in providing technical information and signaling market opportunities to competitors. The pre-grant disclosure contains highly disaggregated information on the focal firm's investment in its innovation (Kim 2018), which can be quite relevant to the competitor's inventions. For example, the Alexa patent mentioned above provides detailed technical information on how to build a smart speaker from different components, the application context of such a device, and how to leverage machine learning to understand natural language. Competitors such as Apple and Google may find such details useful in their own development of smart speakers. In addition, pre-grant disclosure can help competitors identify potential market opportunities. For instance, other IT firms may view the pre-grant disclosure of Amazon's Alexa patent as a signal of the future market demand for virtual assistants and race to make their own R&D investments. Thus, the pre-grant disclosure can stimulate a firm's competitors to innovate in the same domain and to target the same markets. As a result, I expect pre-grant disclosure to increase the IPR overlap between a firm and its peers.

The value of the pre-grant disclosure, however, is not homogeneous. There can be differences based on technological value, which is the extent to which the focal patent destabilizes the technological landscape (Funk and Owen-Smith 2017), and market value, which is the stock market reaction to the grant of focal patent (Kogan et al. 2017). I suggest that because of these differences, the impacts of the disclosure will also be heterogeneous. Reverting to the explanation in which patent examiners' search regarding competitors' patent claims includes the focal firm's pre-disclosures, the focal firm may file patents at the periphery of an important invention simply to limit the patenting of related inventions by competitors (Guellec et al. 2012). In this case, the disclosed information will provide only limited technological and market value to its competitors, who will be more likely to abandon their patent applications if the claims are rejected based on it, since the scope of their applications, if granted, would be too narrow to provide much economic value. Therefore, I expect the knowledge spillover effect to dominate when the pre-grant disclosure has high technological or market value. In particular, I expect an increase of IPR overlap between the focal firm and its peers when the technological or market value of the pre-grant application is high.

Finally, I expect the knowledge spillover effect to be conditional on the *closeness* of competitors to the focal firm. I suggest that this closeness can be differentiated based on (a) the technological space in which the firms innovate and (b) the product markets in which they compete. My rationale for expecting closeness to affect the extent of knowledge spillover is grounded in an absorptive capacity perspective, emphasizing the receiver's ability to recognize the value of new knowledge and to assimilate and apply it (Cohen and Levinthal 1990; Malhotra et al. 2005).

Research Design

Data

To identify firms in the IT industry, I start with the four-digit North American Industry Classification System (NAICS) list in Pan et al. (forthcoming) and remove sub-industries that are not IPR-intensive, such as telecommunications resellers. Table 1 lists the 14 four-digit NACIS codes I use to construct the IT firm sample. The analysis is based on a firm-year-level integrated dataset constructed from the following datasets.

Table 1.
14 Four-digit NAICS IT Industry Sectors

NAICS	Industry
3341	Computer and Peripheral Equipment Manufacturing
3342	Communications Equipment Manufacturing
3343	Audio and Video Equipment Manufacturing
3344	Semiconductor and Other Electronic Component Manufacturing
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing
3346	Manufacturing and Reproducing Magnetic and Optical Media
5112	Software Publishers
5171	Wired Telecommunications Carriers
5172	Wireless Telecommunications Carriers (except Satellite)
5174	Satellite Telecommunications
5179	Other Telecommunications
5182	Data Processing, Hosting, and Related Services
5191	Information Services
5415	Computer Systems Design and Related Services

Patent data. I use the USPTO PatentsView platform—a database that longitudinally links inventors and their organizations, locations, and overall patenting activity—to collect utility patents initially assigned to an IT firm at the time of grant for 1996–2005. Such patents are useful in the focal firm's commercialization of a related technology. I complement each patent with its technological and market values via the datasets compiled by Kogan et al. (2017) and Funk and Owen-Smith (2017).

Financial data. I obtain firms' financial and accounting metrics for 1996–2005 from the Standard & Poor's COMPUSTAT database, which includes 99,000 global securities—covering 99% of the world's total market capitalization—with annual company data history back to 1950.

Merging all 1996–2005 data, I obtain an unbalance panel of data with 5,796 firm-year observations from 1,030 firms. Table 2 provides descriptive information of the sample. Of the sampled firms, 566 had their first pre-grant disclosure in 2001, 160 in 2002, 51 in 2003, 50 in 2004, and 28 in 2005. Such staggered phase-in of the 18-month rule helps to rule out the possibility that an observed change in a focal IT firm's IPR overlap with its peers is a result of other concurrent changes; it is highly unlikely that other concurrent changes follow the same staggered pattern and that a IT firm's exposure to them correlates with its patenting intensity (Hegde et al. 2018).

Methods

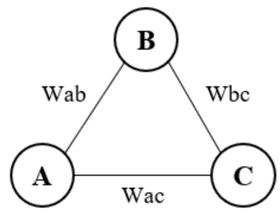
Firm IPR overlap. To characterize a focal IT firm's IPR overlap with its peers, I adopt the idea of the patent claim overlap measure recently developed by USPTO economists (deGrazia et al. forthcoming), which I briefly describe below.

As indicated in Figure 4, a triad is defined based on citations among three granted patents—A, B, and C—each owned by a different firm. Each citation carries a weight determined by the textual similarity of the patent claims in the citing and cited patents. Wab, for example, is the weight measured by the claim similarity of patents A and B. The citation weights are then summed (Wab+Wac+Wbc) to represent the overall claim overlap between one patent and the other two.

Table 2.
Definitions and Descriptive Statistics of Variables

Variable	Definition	Mean	Std. dev.
Overlap	Focal firm's IPR overlap with its peers in year t+1 that may restrict the commercialization of its inventions	0.23	1.05
DisDummy	Equals 1 when the focal firm has its first pre-grant disclosure and then remains 1 until the end of the sample period	0.28	0.45
DisNum	Number of patents the focal firm discloses in year t	12.40	70.00
DisMV	Total market value ($million) of patents disclosed by the focal firm in year t	65.60	369.58
DisTV	Total technological value of patents disclosed by the focal firm in year t	52.80	86.09
PClos	Product market Mahalanobis closeness between the focal firm and its peers in IT industry in 1996–2005, standardized with a mean of 0 and a standard deviation of 1	-0.01	1.01
TClos	Technological Mahalanobis closeness between the focal firm and other firms in IT industry in 1996–2005, standardized with a mean of 0 and a standard deviation of 1	0.04	1.02
RD	R&D expenses scaled by total assets; 0 if R&D expenditures are missing	0.14	0.16
CAPX	Capital expenditures scaled by total assets	0.05	0.05
Size	Firm size as measured by natural logarithm of total assets	4.89	2.23
Lev	Firm leverage as measured by the sum of short-term and long terms debt, scaled by total assets	0.17	0.31
ROA	Income before extraordinary items scaled by total assets	-0.18	0.59
TobinQ	Sum of market value of equity and book value of debt, scaled by total assets	2.86	3.80
MB	Ratio of market value of equity to book value of equity	3.77	6.36

Figure 4
Claim Overlap Calculation Based on a Triad
Note: Each circle represents a patent; the link indicats a citation between two patents.



The intuition of this overlap measure is that each of three firms owns a patent that is similar to those of the other two, which may restrict their commercialization of inventions. As discussed by von Graevenitz et al. (2011), the likelihood of resolving a mutually blocking relationship between any two firms in a triad depends on the actions of the third. Because the negotiation problem in a blocking triad cannot be resolved through independent bilateral negotiation, it is more difficult than in a bilateral relationship, which raises negotiation costs substantially.

As I am interested in IPR overlap that may restrict a firm's commercialization of its inventions, I focus on two types of triad established by its competitors, as indicated in Figure 5. Specifically, the focal firm owns patent A and patents B and C are each owned by a different competitor. In Panel A, patents B and C are linked to patent A as forward citations. The triad is established once patents B and C are granted. In Panel B, patent B is a backward citation of patent A and patent C is a forward citation of patent A. The triad is established once patent C is granted.

For each firm-year in the sample, I first identify all triads, based on the patent citation information. To calculate the claim similarity for a patent pair, I leverage the term frequency-inverse document frequency (TF-IDF) algorithm (Manning and Schutze 2008). Specifically, I transform all patent claims into a TF-IDF-weighted word frequency matrix, with each row representing claims in a focal patent and each column representing the number of times the corresponding word appears in the claims for that patent. The intuition of the TF-IDF algorithm is to increase a word's weight if it appears frequently in a focal patent's claims and to decrease its weight if it also appears in other patents' claims. The weight for each patent pair is the cosine similarity of its TF-IDF vector pair. Combining all three weights gives me the overall claim overlap between the focal firm and its two competitors for the focal triad. To measure the overall claim overlap at the firm-year level, I follow deGrazia et al. (2018), aggregating all triad-level overlap and normalizing it by the number of patents granted for the focal firm-year.

Figure 5
Patent Triads Used in This Study
Note: Each circle represents a patent; the link indicates a citation between two patents.

Econometric model specification. I use a generalized difference-in-differences (Betrand and Mullainathan 2003) based on the quasi-experiment of the enactment of AIPA. As indicated in Hegde et al. (2018), the de facto phase-in of the 18-month disclosure rule is staggered because firms applied for patents at different times after AIPA became effective, which allows me to sharpen my identification of the effect of pre-grant patent disclosures and to isolate it from the effects of other economic or regulatory changes. In addition, as mentioned in Kim (2018), firms didn't necessarily anticipate AIPA's passage, as it was strongly challenged by many individual inventors and even by 25 Nobel laureates in science and economics. This opposition led to many rounds of debate and amendments, causing considerable uncertainty as to whether the mandate would pass. Hence, firms were unlikely to have significantly adjusted their innovation decisions.

The baseline models are as follows:

$$LogOverlap_{it+1} = \alpha + \beta_1 \times Treatment_{it} + Control_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad \text{… Equation (1)}$$

$$LogOverlap_{it+1} = \alpha + \beta_1 \times PClos_i \times Treatment_{it} + \beta_2 \times TClos_i \times Treatment_{it} + Control_{it} + \gamma_i + \delta_t + \varepsilon_{it}\ , \quad \text{… Equation (2)}$$

where *i* denotes firm and *t* denotes year. *Treatment* is my key variable of interest. As shown in Table 2, I construct four variables to indicate the phase-in of the 18-month disclosure rule. *DisDummy* is a dummy variable which equals 1 when the focal firm makes its first pre-grant disclosure and then remains 1 until the end of the sample period. *DisNum* is the number of disclosed pre-grant patents, which I use to measure the differential treatment effect of AIPA. *DisMV* is the total market value of patents disclosed. Specifically, for each disclosed patent, I identify its market value in Kogan et al.'s (2017) dataset, then aggregate the market value of all patents to the firm-year level.[14] *DisTV* is the total technological value of patents disclosed. In particular, for each disclosed patent, I use Funk and Owen-Smith's (2017) dataset to calculate the extent to which the focal patent destabilizes the technological landscape five years from the grant date, then aggregate the technological value of all patents to the firm-year level.[15] For Equation (2), I interact the treatment variables with the closeness in product market and technology between the focal IT firm and its peers in the sample. Specifically, for each firm, I follow Bloom et al. (2013) to calculate the product market (technological) Mahalanobis closeness by using the focal firm's and its peers' sales numbers (granted patent numbers) in different industries (patent technology classes) in 1996–2005.[16] I also include a set of firm characteristics: R&D intensity (*RD*) and capital expenditures (*CAPX*) to capture the allocation of expenditure resources; firm

[14] Please refer to Kogan et al. (2017) for the method of calculating the market value of patents.
[15] The advantage of Funk and Owen-Smith's (2017) measure of technological value is that it distinguishes between inventions that are valuable because they reinforce the status quo and inventions that are valuable because they challenge it. Please refer to their paper for the method of calculating the technological value of patents.
[16] Please refer to Bloom et al. (2013) and Lucking et al. (2018) for detailed discussion on how to calculate these closeness measures.

size (*Size*) to control for operational scale; leverage (*Lev*) to control for potential constraints on investment budget; market-to-book ratio (*MB*) and *TobinQ* to control for potential long-term growth opportunities; and return on assets (*ROA*) to control for financial performance. γ_i is a firm fixed effect, which controls for firm characteristics that do not vary over the sample period. δ_t is a year fixed effect, which absorbs aggregate shocks affecting all firms. In all specifications, I cluster the robust standard errors at the firm level.

Results

I winsorize the variables at the 1% and 99% levels to reduce the impact of outliers. The findings based on Equation (1) are reported in Table 3. In Column 1, *DisDummy* is significantly positive (0.0409, t=4.07, p<0.001), indicating that the knowledge spillover effect dominates. That is, the knowledge disclosed from the focal IT firm's pre-grant patents stimulates competitors to innovate in the same technology domain as the focal IT firm. To explicitly test the validity of the parallel trend assumption in the model specification, I follow Autor (2003) and use a multi-site entry difference-in-differences relative time model as shown below:

$$LogOverlap_{it} = \alpha + \beta_1 \times \sum_{\tau=-6}^{3} \beta_\tau DisDummy_{it+\tau} + Control_{it} + \gamma_i + \delta_t + \varepsilon_{it}\ , \quad \text{… Equation (3)}$$

where $DisDummy_{it+\tau}$ is a dummy that equals 1 for observations in year *t*. Specifically, (a) for $\tau=0$, year *t* is when the focal firm makes its first pre-grant disclosure; (b) for $0<\tau<3$, year *t* is τ years after; (c) for $\tau=3$, year *t* is three or more years after; and (d) for $\tau<0$, year *t* is $|\tau|$ years before the focal firm makes its first pre-grant disclosure. As shown in Figure 6, the coefficients of pre-treatment trends are all insignificant, showing the validity of using the untreated firms as controls.

Figure 6.
Parallel Trend Test of Difference-in-Differences Model Specification

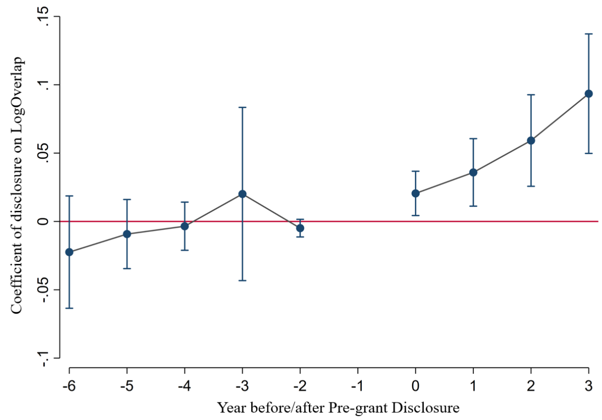


Table 3.
Effect of Pre-grant Disclosure on IPR Overlap

	DV=LogOverlap(t+1)			
Variable	**(1)**	**(2)**	**(3)**	**(4)**
DisDummy	0.0409***			
	(4.07)			
LogDisNum		0.0151***		
		(4.10)		
LogDisMV			0.0115***	
			(4.20)	
LogDisTV				0.00779***
				(4.07)
LogRD	-0.0173	-0.0149	-0.0135	-0.0172
	(-0.40)	(-0.34)	(-0.31)	(-0.40)
LogCAPX	-0.259***	-0.246***	-0.246***	-0.258***
	(-3.95)	(-3.71)	(-3.73)	(-3.95)
LogSize	-0.0253***	-0.0247***	-0.0266***	-0.0253***
	(-3.69)	(-3.62)	(-3.91)	(-3.69)
LogLev	-0.0209	-0.0198	-0.0186	-0.0208
	(-0.85)	(-0.81)	(-0.77)	(-0.85)
ROA	0.00419	0.00490	0.00566	0.00421
	(0.54)	(0.63)	(0.73)	(0.54)
LogTobinQ	-0.0137+	-0.0124+	-0.0132+	-0.0137+
	(-1.85)	(-1.68)	(-1.78)	(-1.85)
MB	0.000631+	0.000655+	0.000717*	0.000633+
	(1.74)	(1.83)	(2.01)	(1.75)
Firm FE	Included			
Year FE	Included			
Intercept	0.191***	0.186***	0.195***	0.191***
	(5.41)	(5.30)	(5.59)	(5.40)
N	5769	5769	5769	5769

Note: Robust standard errors are clustered by firm. t statistics in parentheses.
+p<0.10, * p<0.05, ** p<0.01, *** <0.001.

With this in mind, in Columns 2–4 of Table 3, I explore the differential effects of pre-grant disclosure from two perspectives: disclosure volume and disclosure value. In particular, the knowledge spillover effect is more pronounced when the disclosure volume (0.0151, t=4.10, $p<0.001$) is high. I also find that disclosed knowledge with high market value (0.0115, t=4.20, $p<0.001$) or high technological value (0.00779, t=4.07, $p<0.001$) stimulates competitors to innovate in the same technology domain as the focal firm.

So far, my analysis focuses on the characteristics of pre-grant disclosure by the focal firm and the effects of that disclosure on IPR overlap. Next, I explore how competitors' closeness to the focal firm with respect to technological space and product market affects the observed knowledge spillover effect. Columns 1–4 in Table 4 provide consistent evidence that a competitor's *absorptive capacity* is important in assessing the disclosed knowledge from the focal firm and in assimilating that into its own knowledge base, which in turn facilitates innovation in the same technology domain as that of the focal firm. Interestingly, I find that the absorptive capacity arising from product market closeness is more important for the disclosed knowledge that would destabilize the current technology landscape in the next five years. Given the nature of such knowledge, competitors who are close in the product market with the focal firm would be more likely to assess the value of such knowledge and exploit it for product development.

Table 4.
Effects of Product Market and Technological Closeness on Knowledge Spillover

	DV=LogOverlap(t+1)			
Variable	**(1)**	**(2)**	**(3)**	**(4)**
PClos*DisDummy	0.0127+			
	(1.70)			
TClos*DisDummy	0.0279***			
	(3.52)			
PClos* LogDisNum		0.00228		
		(0.86)		
TClos* LogDisNum		0.00562**		
		(2.97)		
PClos* LogDisMV			0.00112	
			(0.58)	
TClos* LogDisMV			0.00484***	
			(3.32)	
PClos* LogDisTV				0.00240+
				(1.69)
TClos* LogDisTV				0.00523***
				(3.52)
LogRD	-0.0154	-0.0122	-0.0120	-0.0152
	(-0.36)	(-0.28)	(-0.28)	(-0.35)
LogCAPX	-0.241***	-0.249***	-0.248***	-0.241***
	(-3.76)	(-3.86)	(-3.82)	(-3.75)
LogSize	-0.0223**	-0.0218**	-0.0224**	-0.0223**
	(-3.24)	(-3.13)	(-3.24)	(-3.24)
LogLev	-0.0227	-0.0224	-0.0222	-0.0228
	(-0.94)	(-0.92)	(-0.92)	(-0.94)
ROA	0.00421	0.00354	0.00403	0.00420
	(0.54)	(0.45)	(0.52)	(0.54)
LogTobinQ	-0.00960	-0.0119	-0.0121	-0.00965
	(-1.31)	(-1.61)	(-1.63)	(-1.31)
MB	0.000606+	0.000613+	0.000651+	0.000607+
	(1.65)	(1.69)	(1.81)	(1.65)
Firm FE	Included			
Year FE	Included			
Intercept	0.171***	0.172***	0.175***	0.171***
	(4.86)	(4.84)	(4.93)	(4.86)
N	5769	5769	5769	5769

Note: Robust standard errors are clustered by firm. t statistics in parentheses.
+p<0.10, * p<0.05, ** p<0.01, *** <0.001.

Discussion

Conclusion. This study outlines two competing predictions of how a firm's pre-grant patent disclosure will affect its IPR overlap with competitors: (a) a constraining influence due to patent examiners' evaluations that take the pre-grant disclosures into account while assessing competitors' patent claims and (b) knowledge spillover when technical information and market signals are revealed to competitors. The empirical evidence indicates that the knowledge spillover effect dominates—especially when the technological and market values of the disclosure are high—and is more pronounced when the competitors are close to the focal firm in technology space and product market.

Contribution. This study contributes to the emerging scholarly conversation on the dynamics of innovation in the IT industry. The current literature provides evidence on how financing and product market competition can affect an IT firm's innovation input (e.g., R&D spending) and output (e.g., number of patents granted) (Kim et al. 2016; Pan et al. forthcoming). This study, in contrast, reveals the innovation interdependency among IT firms in terms of IPR and uncovers the underlying mechanism by which such interdependency evolves. Thus, it provides more nuanced evidence of the dynamics of innovation in the IT industry.

This study also enriches the understanding of patent thickets. The current conversation among economists, legal scholars, and policy makers mainly focuses on adverse effects and potential solutions. This study shifts that focus by examining the micro-foundation with regard to the formation of patent thickets in the IT industry. Specifically, it indicates that the knowledge spillover due to technical information and market signals being revealed to competitors via pre-grant patent disclosure increases the focal IT firm's overlapping IPR. That indicates that disclosure is an important input into the optimal patent policy design in order to address patent thickets.

Finally, I provide insights on the conditions under which the knowledge spillover effect—and consequently IPR overlap—are likely to be more pronounced. Specifically, I find a duality of competitors' *motivation* and *capability* explains the extent of IPR overlap. Competitors are more likely to pursue and patent similar digital innovations if the focal firm's patent has high technological or market value and are more likely to be able to pursue similar innovations if they have the absorptive capacity to assess, assimilate, and exploit the knowledge underlying the disclosed patents. This absorptive capacity is likely to be greater when the competitors are in a similar technological space and product market.

Limitation and future research. In this study, I focus on public firms in the IT industry to examine the formation of patent thickets. However, due to the increasing dependence of innovation on software, digital patents are increasingly important in industries well beyond the traditional definition of electronics and IT (Branstetter et al. 2018). One would therefore expect a cascading adverse effect of thickets of digital patents on traditional manufacturing industries such as automobiles, aerospace, medical devices, and pharmaceuticals. It would be interesting to explore how firms in non-IT sectors react to this threat and assemble their digital patent portfolios, which in turn may affect the dynamic of patent thicket formation for digital patents.

Additionally, the share of young firms in economic activity has been on a secular decline since the 1980s (Decker et al. 2016; Furman and Orszag 2018). One potential explanation is that patent thickets, especially for digital patents, increase the barrier of technology entry. Since young firms typically have limited resources, it is worth future study to understand whether they could leverage the same IP strategy—assembling a patent portfolio—that established firms use to navigate through patent thickets. If so, to what extent do young firms contribute to the formation of patent thickets?

In a recent survey of over 5000 American manufacturing firms (Arora et al. 2016), 49% report that, between 2007 and 2009, their most important new product originated from outside sources such as customers, suppliers, and technology specialists (i.e., universities, independent inventors, and R&D contractors). With such a shift toward external sources of invention, it would be interesting to compare how externally acquired patents and internally generated patents affect the formation of patent thickets.

Essay 3

Democratizing Venture Capital Financing for Innovation: Crowdfunding under Intellectual Property Rights Governance

Abstract

Crowdfunding platforms such as Kickstarter are increasingly important for financing innovation and entrepreneurship, with the potential to generate high-quality signals that attract venture capitalists (VCs) to new regions. Unfortunately, realizing this benefit of crowdfunding platforms involves a growing intellectual property rights (IPR) risk from patent assertion entities (PAEs)—the so-called “patent trolls”—which often send bad-faith demand letters to thousands of businesses, counting on their lack of experience with the patent system in order to coerce them into paying settlements. By leveraging a quasi-experiment—the enactment of state anti-PAE laws in 2010–2017—I use a multi-site entry difference-in-differences relative time model and find strong evidence that a state’s enactment of anti-PAE laws is critical in realizing two crowdfunding benefits: attracting VC investment into the state and diversifying the investment across industries within the state. This study widens the focus of the crowdfunding literature from market efficiency to the democratization of the flow of VC financing, while surfacing the critical role of institutional governance of IPR risk in achieving this benefit.

Keywords: Crowdfunding, venture capital, innovation, entrepreneurship, patent trolls, intellectual property rights governance

Research Problem Formulation

Crowdfunding platforms such as Kickstarter are increasingly important for financing innovation and entrepreneurship, which in turn generates extensive scholarly conversation on how to increase their market efficiency, since they are often viewed as a two-sided market between entrepreneurs and funders (Agrawal et al. 2014). Spanning the crowdfunding project lifecycle, scholars are interested in (a) the antecedents of entrepreneurs' participation in a crowdfunding project (e.g., Belleflamme et al. 2014); (b) funders' decision-making processes (e.g., Burtch et al. 2013; Hong et al. forthcoming); (c) funders' heterogeneity and dynamics (e.g., Lin et al. 2014); and (d) key factors in reaching a project's funding goal (e.g., Mollick 2014).

Recent scholarly discussion, however, has shifted its focus from market efficiency to the interaction between crowdfunding and professional investors. For example, VCs who once only funded entrepreneurs with certain educational, social, and professional characteristics and from only a few regions (such as New York, Boston, and the San Francisco Bay Area) are increasingly leveraging the high-quality signals from entrepreneurial campaigns on crowdfunding platforms to invest in a more diversified group of entrepreneurs (Babich et al. 2018; Drover et al. 2017; Roma et al. 2018; Ryu et al. 2018; Sorenson et al. 2016). Thus, crowdfunding not only attracts funders to finance entrepreneurs through the platform itself, but also makes entrepreneurs more visible to professional investors and democratize their access to such investment.

Unfortunately, realizing this benefit involves a growing intellectual property rights (IPR) risk from patent assertion entities (PAEs)—the so-called "patent trolls"—who acquire a large portfolio of patents but do not use them for any research or product development (Cohen et al. 2016), only to extract payments from alleged infringers with deep pockets via fraudulent claims (Cohen et al. 2016; Hagiu and Yoffie 2013). In general, there has been ample documented evidence of the adverse impacts of PAEs on innovation and entrepreneurship. For instance, once targeted by PAEs, startups delay their hiring, make changes in their products, shift their business strategy, lose valuation from inventors, and even shut down the business line or the entire business (Chien 2013). For established firms, attack by PAEs makes them reduce R&D investment by 25% and divert resources from new product development (Cohen et al. 2016).

Entrepreneurs on crowdfunding platforms have also become targets of PAE attacks. For instance, Frebble is a Kickstarter project, developed by Holland Haptics, that allows people to hold hands with someone at a distance.[17] In 2015, right after Holland Haptics successfully pledged €12,260, it was sued by a PAE called TZU Technologies,[18] which claimed infringement of its patent US6368268B1. Kickstarter's general counsel, Michal Rosenn, who has been in touch with Holland Haptics, indicated that "[t]his is a huge problem…They're a tiny team, with very little money… It's exactly small businesses that are most vulnerable, because most can't afford to litigate. Many businesses get liquidated because of patent trolls."[19]

To extract payments, PAEs often start by sending bad-faith demand letters to thousands of businesses. These letters lack the required patent information and request an unreasonable license fee in an unreasonably short period of time, but as long as a few businesses quickly settle, it earns the PAE a good return on its investment in patents that are often weak and of limited validity (American Intellectual Property Law Association 2013). To attract potential funders, crowdfunding platforms require entrepreneurs to disclose their entrepreneurial campaign information. Such disclosure, however, could draw threats from PAEs, who leverage the

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[17] Retrieved May 1, 2019, from https://www.kickstarter.com/projects/396691740/hold-hands-online-when-you-miss-someone.

[18] Retrieved May 1, 2019, from http://cdn.arstechnica.net/wpcontent/uploads/2015/07/TZU.Kickstarter.Complaint.pdf.

[19] Retrieved May 1, 2019, from https://arstechnica.com/tech-policy/2015/10/teledildonics-patent-troll-backs-down-from-lawsuit-against-kickstarter.

information to scan for any possible indication that a campaign can be construed to infringe patents in their portfolios.

Under such threats, entrepreneurs tend to disclose less information on the crowdfunding platforms, while VCs avoid investing, seeing PAEs as a major deterrent (Feldman 2014). If this happens, the entire process of facilitating entrepreneurs' access to professional investors via crowdfunding signaling will break down. This study joins the scholarly conversation on crowdfunding platforms—specifically, on their role in democratizing entrepreneurial financing—while differentiating itself from past work by addressing the IPR threats brought by PAEs. Specifically, it aims to answer the question: *Does the institutional governance against PAEs affect the ability of crowdfunding platforms to attract VC investment and, if so, how?*

Crowdfunding as Signals for VCs and PAEs

Technology ventures being inherently uncertain, VCs seek signals of potential success in founders' ability, background, and past successes (Mollick 2014). They focus therefore on entrepreneurs with certain educational, social, and professional characteristics and from a small number of regions (such as New York, Boston, and the San Francisco Bay Area). Recently, however, this approach has changed due to the growing influence of crowdfunding platforms. Specifically, the high-quality signals from entrepreneurial campaigns on crowdfunding platforms empower VCs to evaluate entrepreneurs' ability (e.g., their ideas and their ability to build a product and deal with logistics and suppliers) and to assess demand prior to the launch of a new product, which in turn enables them to invest in a more diversified group of ventures (Babich et al. 2018; Drover et al. 2017; Roma et al. 2018; Ryu et al. 2018; Sorenson et al. 2016). However, the signals from entrepreneurial campaigns on crowdfunding platforms are as available to PAEs as they are to VCs, making it easy for PAEs to identify targets with deep pocket and promising market demand. As policy makers in various states have become increasingly aware of such IPR risk, they have designed institutional governance to address it.

Institutional Governance of PAEs

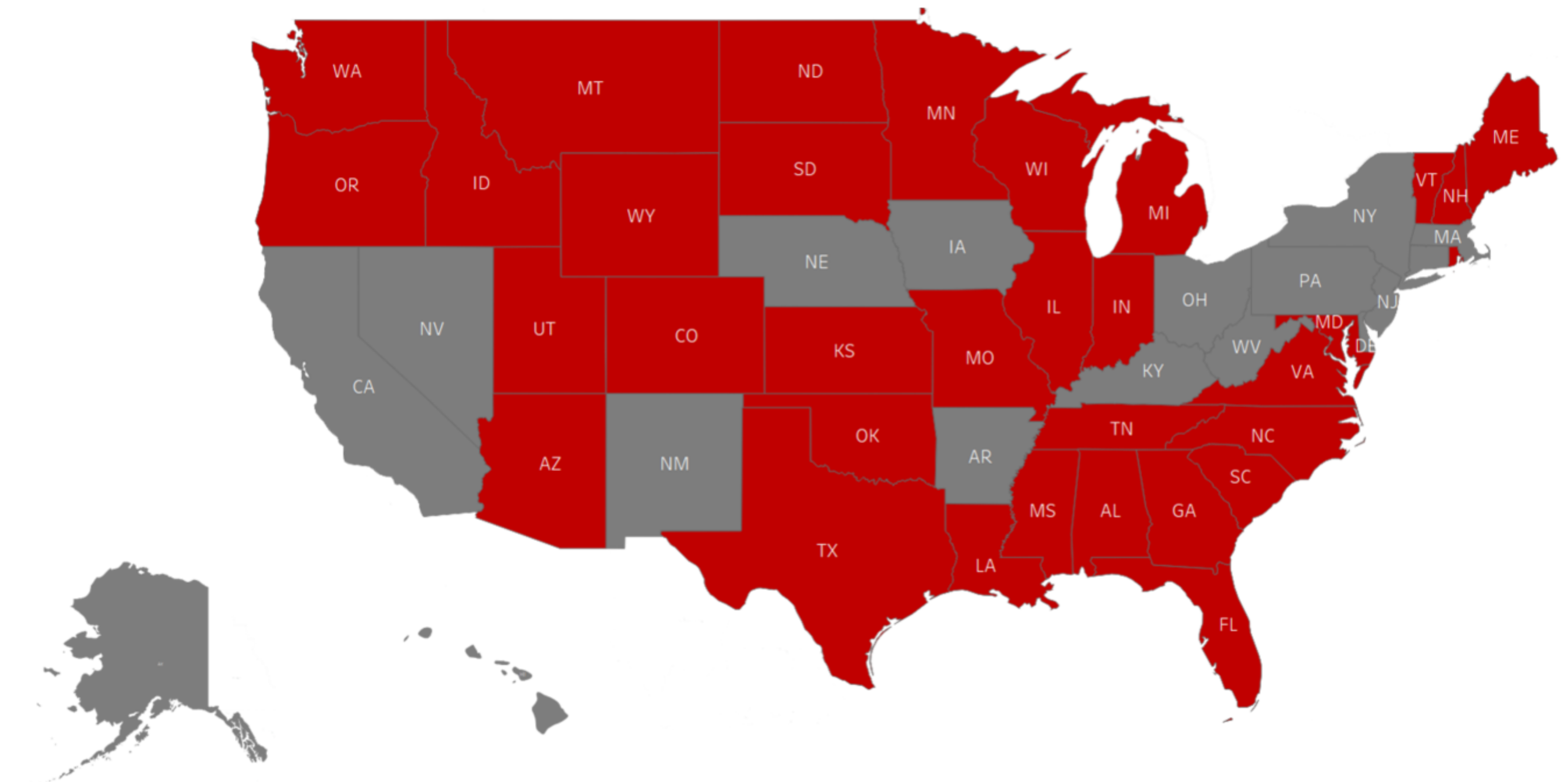
Although businesses had the right to sue PAEs even before the enactment of anti-PAE laws, the courts could barely penalize PAEs, as they are limited liability business entities. Thus, the plaintiff not only could not receive any remedy, but also had to pay the litigation costs. As noted by the anti-PAE law in Vermont (9 V.S.A. § 4195), "A business that receives a letter asserting such claims faces the threat of expensive and protracted litigation and may feel that it has no choice but to settle and to pay a licensing fee, even if the claim is meritless. This is especially so for small and medium-sized companies and nonprofits that lack the resources to investigate and defend themselves against infringement claims. We seek to change the calculations of patent trolls in Vermont by increasing the potential costs of sending out mass demand letters."

Anti-PAE laws change that situation. As of 2017, 33 US states have enacted such laws to curtail bad-faith demand letters, as shown in Figure 1.

These laws share two critical components (Appel et al. forthcoming). First, they aim to address bad-faith patent-infringement assertions made via demand letters by allowing courts to impose penalties on the senders of such letters. Second, they cover any target firm located in the state, regardless of where the sender of the letter is located. However, the laws vary in how to penalize PAEs via bond requirement and punitive damage remedy and in who can initiate legal action against a PAE, as indicated in Table 1. Specifically:

For bond requirement, 18 of the 33 state laws (55%) establish that if a court finds that a business within the focal state has been the target of bad-faith demand letters, then the court can request

Figure 1.
Enactment of Anti-PAE Laws as of 2017
(states with anti-PAE laws indicated in red)



the sender of those letters to post a bond. In Georgia, for example, “a target may move that a bad faith assertion of patent infringement has been made in violation of this article and request that a protective order be issued as described in this Code section. Upon such motion and a finding by the court that a target has established a reasonable likelihood that an author of a demand letter has made a bad faith assertion of patent infringement, the court shall require the author of the demand letter to post a bond in an amount equal to a good faith estimate of the target's expenses of litigation, including an estimate of reasonable attorney's fees, conditioned upon payment of any amounts finally determined to be due to the target. A hearing shall be held if either party so requests. A bond ordered pursuant to this Code section shall not exceed $250,000.00” (O.C.G.A. § 10-1-772).

For punitive damage remedy, 20 of the 33 state laws (61%) establish that the recipient of the bad-faith demand letters can be awarded damages exceeding simple compensation and awarded to punish the defendant. In Georgia, for example, the penalty can be “in an amount equal to $50,000.00 or three times the combined total of damages, costs, and fees, whichever is greater” (O.C.G.A. § 10-1-773).

For legal action against PAEs, 24 out of the 33 state laws (73%) establish that the recipient of the bad-faith demand letters, in addition to the state’s Attorney General, can bring an action individually (private action) against a PAE. In Georgia, for example, “Any person who suffers injury or damages as a result of a violation of this article may bring an action individually against the person or persons engaged in such violation under the rules of civil procedure to seek equitable injunctive relief and to recover his or her general and exemplary damages sustained as a consequence thereof in any court having jurisdiction over the defendant” (O.C.G.A. § 10-1-773).

Table 1.
Enactment Dates and State Differences of State Anti-PAE Laws

State	Date enacted	Bond requirement	Punitive damage remedy	Private action
AL	3/18/2014		Yes	Yes
AZ	3/24/2016			Yes
CO	6/5/2015			
FL	6/2/2015	Yes	Yes	Yes
GA	4/15/2014	Yes	Yes	Yes
ID	3/26/2014	Yes	Yes	Yes
IL	8/26/2014			Yes
IN	5/5/2015	Yes	Yes	Yes
KS	5/20/2015			
LA	5/28/2014			
MD	5/5/2014		Yes	Yes
ME	4/14/2014	Yes	Yes	Yes
MI	1/6/2017	Yes	Yes	Yes
MN	4/29/2016			
MO	7/8/2014			Yes
MS	3/28/2015	Yes	Yes	Yes
MT	4/2/2015	Yes	Yes	Yes
NC	8/6/2014	Yes	Yes	Yes
ND	3/26/2015	Yes	Yes	Yes
NH	7/11/2014	Yes		Yes
OK	5/16/2014	Yes	Yes	
OR	3/3/2014			
RI	6/14/2016	Yes	Yes	Yes
SC	6/9/2016	Yes		Yes
SD	3/31/2014	Yes	Yes	Yes
TN	5/1/2014	Yes	Yes	Yes
TX	6/17/2015			
UT	4/1/2014	Yes	Yes	Yes
VA	5/23/2014			
VT	5/22/2013	Yes	Yes	Yes
WA	4/25/2015			
WI	4/23/2014		Yes	Yes
WY	3/11/2016		Yes	Yes

Research Design

Data

My analysis is based on state-quarter level data constructed from the following datasets:

State anti-PAE law data. I download the full text of anti-PAE laws for 33 states as of 2017 from LexisNexis. I code each law based on the two dimensions shown in Table 1: penalty (bond requirement and punitive damage remedy) and private right to take legal action (private action).

Venture capital investment data. VC investment information is from Thomson Reuters's VentureXpert database, which characterizes VC investments into portfolio companies, regardless of the investment outcome. Consistent with Sorenson et al. (2016) and Appel et al. (forthcoming), I focus on early-stage VC rounds raised by firms with headquarters in the United States. I use the number of VC investments within a state as a proxy for VC activity in that state.

Kickstarter campaign data. I draw 2010–2017 crowdfunding data from Kickstarter—the largest rewards-based crowdfunding platform by traffic, number of backers, and total dollars pledged (Yu et al. 2017) and has been used by Sorenson et al. (2016) as a proxy for crowdfunding activity—to understand the relationship between state-level crowdfunding and VC investments. I identify the geographic location for each Kickstarter project and use the number of Kickstarter projects ended within a state as a proxy for crowdfunding activity in that state. To identify Kickstarter campaigns that are of interest to VCs, I select successful campaigns that (a) are in the technology category (Sorenson et al. 2016), (b) have above the median number of backers and above the median amount of funding target (Babich et al. 2018; Roma et al. 2018), and (c) have below the median amount of VC investment (Babich et al. 2018).

Patent data. I use the USPTO PatentsView platform—a database that longitudinally links inventors and their organizations, locations, and overall patenting activity—to collect utility patents associated with a state, based on the location of the first assignee at the time of grant, for 2010–2017.

Patent litigation data. I obtain patent cases for patent district courts in each state from LexMachina, an analytics platform that includes litigation information regarding patent, trademark, copyright, antitrust, securities, commercial, employment, product liability, and bankruptcy.

State economic indicator data. Data on the per-capita personal income and GDP for each state-quarter 2010–2017 comes from the Bureau of Economic Analysis database.

Self-employment data. Self-employment numbers for each state-quarter from 2010–2017 are extracted from the Integrated Public Use Microdata Series (IPUMS) Current Population Survey (CPS), administered monthly by the US Bureau of the Census to over 65,000 households. This survey gathers information on education, labor force status, demographics, and other aspects of the US population and is widely used by demographers, economists, sociologists, and other population-related researchers. It is also the basis upon which monthly federal unemployment statistics are calculated.

Aggregating all data to the state-quarter level, I obtain 1,500 observations from 2010–2017 for analysis. Table 2 provides descriptive information on the sample.

Table 2.
Definitions and Descriptive Statistics of Variables

Variable	Definition	Mean	Std. dev.
VC	Number of VC investments in the categories of communication, computer hardware, computer software, consumer-related, industrial/energy, internet-specific, and semiconductor/electronic	17.88	66.49
IndexVC	Herfindhal index of VC investments in the categories of communication, computer hardware, computer software, consumer-related, industrial/energy, internet-specific, and semiconductor/electronic	0.69	0.26
KS	Number of successful Kickstarter campaigns that (a) are in the technology category, (b) have above the median number of backers and above the median amount of funding target, and (c) have below the median of VC investment	1.03	2.57
GDP	State GDP ($million)	329441.60	416979.90
Income	State per-capita personal income	45091.79	8364.99
Patent	Number of utility patents associated with a state, based on the location of the first assignee at the time of grant	563.22	1280.29
Patent Litigation	Number of patent litigations assigned to the state patent district courts	29.17	78.22
Self-employment	Number of self-employed individuals in the state based on CPS survey sample (N=65,000 households)	137.72	97.77

Methods

Matching between Kickstarter campaigns and VC investments. VCs invest in some industries for which one would not see Kickstarter campaigns. For example, Kickstarter excludes campaigns for biotechnology. I therefore restrict the VC industries included to those that matched Kickstarter campaigns in the category of technology and confirm those matches via text analysis of the descriptions of Kickstarter campaigns and VC investments. Specifically, I match Kickstarter campaign categories to VC investments industries via two algorithms: term frequency-inverse document frequency (TF-IDF) (Manning and Schutze 2008) and Doc2Vec (Le and Mikolov 2014).

To prepare the inputs for these two algorithms, I construct a corpus that includes descriptions of (a) Kickstarter campaigns that belong to one of a set of mutually exclusive Kickstarter categories (art, comics, crafts, dance, design, fashion, food, games, journalism, music, photography, publishing, technology, theater, and film and video) and (b) VC investments that are associated with one of a set of mutually exclusive VC industries (biotechnology, business services, communications, computer hardware, computer software, consumer-related, industrial/energy, internet-specific, medical/health, and semiconductor/electronic). I tokenize this corpus by (a) removing punctuation, (b) lowercasing all letters, (c) keeping words with length of 3–15 letters, and (d) stemming all words. After vectorization, I create a word frequency matrix with each row representing a Kickstarter campaign/VC investment description and each column representing the number of times the corresponding word appears in the description.

I apply the TF-IDF algorithm to this word frequency matrix to convert it into a TF-IDF-weighted word frequency matrix. The intuition of the TF-IDF algorithm is to increase a word's weight if it appears frequently in a particular Kickstarter campaign/VC investment description and decrease its weight if it also appears in other Kickstarter campaign/VC investment descriptions.

Next, I aggregate the TF-IDF-weighted word frequency matrix to the Kickstarter-category or VC-industry level. Specifically, I take an average across the rows for Kickstarter campaigns related to a particular category or for VC investments in a particular industry to produce a single vector of weighted word frequency for each. I use these vectors to calculate the cosine similarity between each Kickstarter category and VC industry, ending up with 150 cosine similarity values (15 Kickstarter categories * 10 VC industries). I rank these values—with 1 representing the highest similarity value—leading to a similarity ranking matrix, as shown in Figure 2. To identify the VC industries that correspond closely to a Kickstarter technology category, I select communications, computer hardware, computer software, consumer-related, internet-specific, and semiconductor/electronics, as they are among the top 10 in the similarity ranking.

A potential problem with the TF-IDF algorithm is that it is based on a bag-of-words model. Therefore, it does not take semantics and word order into consideration. To address these weaknesses, I applied the Doc2Vec algorithm to the word frequency matrix so that each Kickstarter campaign/VC investment description is mapped to a unique vector. As in the TF-IDF process, I (a) take an average across the rows for Kickstarter campaigns related to a particular category or for VC investments in a particular industry to produce a single vector for each, (b) calculate pairwise cosine similarity, and (c) generate a similarity ranking matrix, as shown in Figure 3. In addition to the VC industries selected by the TF-IDF algorithm, I include industrial/energy, as the Doc2Vec algorithm indicates that it corresponds closely to a Kickstarter technology category.

Figure 2.
The Ranking of TF-IDF Pairwise Cosine Similarity Values between Kickstarter Categories and VC Industries

VC

	Biotechnology	Business Serv.	Communications	Computer Hardware	Computer Software	Consumer Related	Industrial/Energy	Internet Specific	Medical/Health	Semiconductor/Electr
Art	116	73	139	89	92	47	106	67	122	94
Comics	190	167	185	181	164	154	195	149	192	193
Crafts	144	114	168	104	127	22	129	65	110	111
Dance	158	151	172	170	179	118	187	174	138	156
Design	107	59	61	36	42	8	48	34	50	26
Fashion	157	76	166	126	137	24	180	51	121	143
Film & Video	81	43	77	62	52	33	123	39	64	88
Food	135	68	112	91	96	9	99	49	125	148
Games	152	74	97	60	57	54	133	55	173	80
Journalism	131	23	45	38	27	29	155	14	87	130
Music	161	79	103	90	86	41	136	63	105	124
Photography	178	102	160	108	109	66	159	72	140	132
Publishing	83	53	101	71	46	35	162	31	78	146
Technology	75	15	6	2	3	5	25	4	32	7
Theater	183	134	163	176	177	100	189	153	171	169

Figure 3.
The Ranking of Doc2Vec Pairwise Cosine Similarity Values between Kickstarter Categories and VC Industries

Vc

Ks	Biotechnology	Business Serv.	Communications	Computer Hardware	Computer Software	Consumer Related	Industrial/Energy	Internet Specific	Medical/Health	Semiconductor/Electr
Art	146	113	67	38	46	23	71	26	122	69
Comics	176	172	154	108	121	80	166	85	173	160
Crafts	126	135	83	41	55	13	52	28	97	53
Dance	182	175	157	130	140	102	167	104	177	165
Design	91	84	27	12	19	8	18	15	44	11
Fashion	156	144	99	64	78	14	95	34	137	77
Film & Video	136	124	63	57	51	32	96	33	118	90
Food	142	133	73	66	65	9	62	31	129	81
Games	171	147	74	48	37	43	119	35	158	89
Journalism	106	61	25	24	17	16	75	7	79	59
Music	178	168	132	98	100	56	149	70	170	134
Photography	164	159	105	68	72	40	125	39	148	103
Publishing	131	141	87	50	49	30	117	29	115	101
Technology	58	36	4	3	2	6	10	1	22	5
Theater	139	153	110	88	82	45	123	54	143	116

Econometric model specification. I use a multi-site entry difference-in-differences relative time model (Autor 2003) based on the quasi-experiment of the enactment of state anti-PAE laws. As indicated in Appel et al. (forthcoming), this empirical setting allows the same state to be part of the treatment and control groups at different times. Specifically, at any year-quarter *t*, the control group includes both states that passed anti-PAE laws after *t* (but before 2018)—therefore will be treated eventually—and states that are never treated (because they never passed an anti-PAE law during the sample period).

To investigate how the anti-PAE laws affect the relationship between Kickstarter campaigns and VC investment, I construct two baseline models:

$$\begin{aligned} LogVC_{i(t+1)} = \alpha + \textstyle\sum_{\tau=-4}^{4} \beta_\tau PAE_{it+\tau} \times LogKS_{it} + \beta_1 \times LogKS_{it} + \beta_2 \times LogGDP_{it} \\ +\beta_3 \times LogIncome_{it} + \beta_4 \times LogPatent_{it} + \beta_5 \times LogPatentLitigation_{it} \\ +\beta_6 \times LogSelfEmployment_{it} + \gamma_i + \delta_t + \varepsilon_{it} \end{aligned}$$

…… Equation (1)

$$\begin{aligned} IndexVC_{i(t+1)} = \alpha + \textstyle\sum_{\tau=-4}^{4} \beta_\tau PAE_{it+\tau} \times LogKS_{it} + \beta_1 \times LogKS_{it} + \beta_2 \times LogGDP_{it} \\ +\beta_3 \times LogIncome_{it} + \beta_4 \times LogPatent_{it} + \beta_5 \times LogPatentLitigation_{it} \\ +\beta_6 \times LogSelfEmployment_{it} + \gamma_i + \delta_t + \varepsilon_{it}, \end{aligned}$$

…… Equation (2)

where *i* denotes state and *t* denotes year-quarter. $PAE_{it+\tau}$ is a dummy that equals 1 for observations in quarter *t*. Specifically, (a) for $\tau=0$, quarter *t* is when the anti-PAE law is enacted; (b) for $0<\tau<4$, quarter *t* is τ quarters after the enactment; (c) for $\tau=4$, quarter *t* is four or more quarters after; and (d) for $\tau<0$, quarter *t* is $|\tau|$ quarters before the anti-PAE law is enacted. γ_i is a state fixed effect, which controls for state characteristics that do not vary over the sample period. δ_t is a year-quarter fixed effect, which absorbs aggregate shocks affecting all states. In all specifications, I cluster the robust standard errors at the state level. Table 2 provides definitions of the other variables.

Results

Main result. I first explore whether the enactment of state anti-PAE laws helps the signals from Kickstarter attract VC investment into the state. After controlling for several state-specific dynamic factors, the log-transformed linear regression analysis (Model 2 in Table 3) indicates that two quarters after the law is enacted, a 1% increase in the number of Kickstarter campaigns in a state-quarter is related to a 0.359% (t=3.07, p<0.01; Model 2 in Table 4) increase in the number of VC investments in the following state-quarter. The coefficients of pre-treatment trends are all insignificant, showing the validity of using the untreated states as controls.

Robustness tests. I conduct a battery of robustness analyses,[20] as shown in Table 3, to reduce the possibility that my findings are due to confounding factors. First, as mentioned by Sorenson et al. (2016), the number of Kickstarter campaigns could be endogenous. As Kickstarter campaigns in comics and dance categories are of no interest to VC investors, I adopt a similar instrument variable—the number of successful Kickstarter campaigns in those categories—and reestimate the model. The relationship is even stronger (0.651%, z=3.08, p<0.01; Model 3 in Table 4). Next, to tease out the possibility that state-specific VC investment trends may contaminate the results, I include the state-specific linear trend in the model specification. Again, I see a strong relationship (0.527%, z=2.74, p<0.01; model 4 in Table 4) between Kickstarter campaigns and VC investment (see Figure 4). Another concern arises from the possibility that the finding is due to the timing of the enactment of anti-PAE laws being related to both Kickstarter campaigns and VC investments. I therefore conduct a placebo test (Model 5 in Table 4). That is, I assume that the anti-PAE laws were enacted two years earlier than their actual enactment date across states.

[20] Appel et al. (forthcoming) indicate that enactment of the laws is driven by persistent characteristics of the states (captured by the state fixed-effects in the models) rather than by changes in their economic conditions.

In this hypothetical scenario, the empirical evidence (all post-enactment coefficients are insignificant) helps rule out this explanation.

Table 3.
Model Specifications to Evaluate Effect of State Anti-PAE Law Enactment on the Relationship between Kickstarter Campaigns and VC Investment in a State-Quarter

Model	Specification	Rationale
Model 1	Log-OLS without leading and lagging PAE indicators	Baseline analysis
Model 2	Log-OLS with leading and lagging PAE indicators	Baseline analysis
Model 3	Log-2SLS based on the instrument variable of KS activity in the categories of dance and comics	KS activity could be endogenous
Model 4	Log-2SLS with state-specific linear trend	State-specific VC investment trend may contaminate results
Model 5	Log-2SLS with state-specific linear trend based on a placebo test that assumes enactment 2 years earlier than the actual enactment date	A possibility that the finding is due to the enactment timing of anti-PAE laws being related to both Kickstarter campaigns and VC investment

Figure 4.
Effect of State Anti-PAE Law Enactment on the Relationship between Number of Kickstarter Campaigns and Number of VC Investments in a State-Quarter
Note: The coefficients and 95% confidence intervals are derived from Model 4 in Table 4.

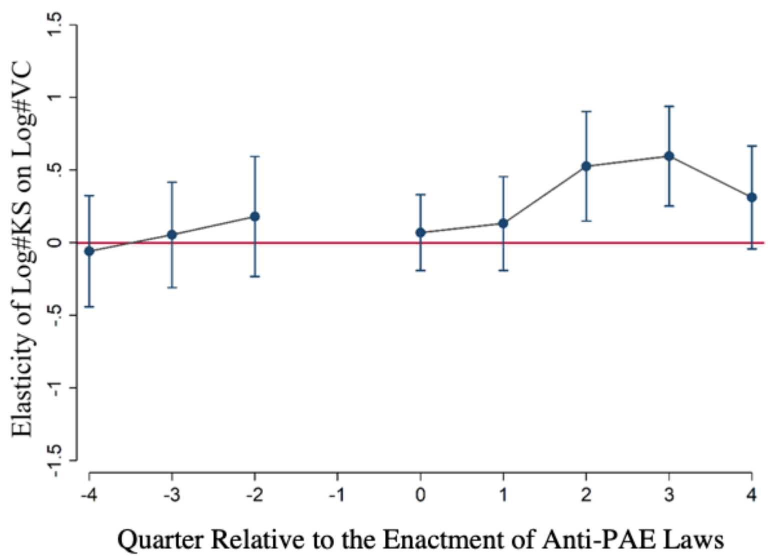


Table 4.
Effect of State Anti-PAE Law Enactment on the Relationship between Number of Kickstarter Campaigns and Number of VC Investments in a State-Quarter

	DV= Log (# VC Investments)				
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log KS	0.0266	-0.0934	0.0187	-0.220	-0.333
	(0.63)	(-1.54)	(0.06)	(-0.61)	(-0.69)
PAE(-4) * Log KS		0.231	0.0762	-0.0586	-0.0839
		(1.55)	(0.36)	(-0.30)	(-0.17)
PAE(-3) * Log KS		-0.000792	0.0945	0.0547	0.0641
		(-0.01)	(0.53)	(0.30)	(0.12)
PAE(-2) * Log KS		-0.0148	0.252	0.180	-0.459
		(-0.10)	(1.18)	(0.86)	(-0.83)
PAE(-1) * Log KS			Omitted as baseline		
PAE(0) * Log KS		0.0840	0.149	0.0697	0.299
		(0.73)	(1.17)	(0.52)	(0.89)
PAE(1) * Log KS		0.0599	0.142	0.133	-0.0495
		(0.46)	(0.79)	(0.80)	(-0.14)
PAE(2) * Log KS		0.359**	0.651**	0.527**	0.183
		(3.07)	(3.08)	(2.74)	(0.56)
PAE(3) * Log KS		0.343*	0.668***	0.596***	0.251
		(2.38)	(3.67)	(3.41)	(0.87)
PAE(4+) * Log KS		0.161*	0.358*	0.312+	0.350
		(2.09)	(2.31)	(1.73)	(1.12)
Log GDP	1.317*	1.182+	0.891	0.205	0.502
	(2.07)	(1.93)	(1.58)	(0.21)	(0.50)
Log Income	-0.333	-0.294	-0.658	0.544	0.0302
	(-0.26)	(-0.23)	(-0.48)	(0.35)	(0.02)
Log Patent	0.227**	0.219*	0.178*	0.133+	0.133+
	(2.70)	(2.54)	(2.04)	(1.94)	(1.89)
Log Patent Litigation	0.00208	0.000505	-0.00451	0.0204	0.0234
	(0.07)	(0.02)	(-0.15)	(0.66)	(0.73)
Log Self Employment	-0.0556	-0.0476	-0.0194	-0.0684	-0.0474
	(-0.62)	(-0.53)	(-0.20)	(-0.52)	(-0.38)
State FE	Y	Y	Y	Y	Y
Year_Quarter FE	Y	Y	Y	Y	Y
State Trend FE				Y	Y
N	1500	1500	1500	1500	1530

Note: *PAE* indicators identify quarters *t*-4, *t*-3, …, *t*, …, *t*+3, and *t*>=4 for states that enact an anti-PAE law, where *t* is the quarter in which the law is enacted. States that enacted an anti-PAE law in the fourth quarter of 2016 or later, for which I observe fewer than four post-treatment observations, are excluded from the treatment group. Robust standard errors are clustered by state. z statistics in parentheses. +p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Concentration of VC investment. One might wonder whether the VC investments attracted by the signals on entrepreneurial activity from Kickstarter (a) flow only to those industries in a state in which VCs specialize or (b) transcend such specialization. I construct an industry concentration index of VC investment and examine whether the enactment of state anti-PAE laws helps Kickstarter attract VC investment across industries into the state. As in the previous analysis, I conduct a range of tests based on the model specifications in Table 3 and find a strong and robust negative relationship between Kickstarter campaigns in a state and the industry concentration index of VC investment flowing into that state. Specifically, once the anti-PAE law is enacted, a 1% increase in the number of Kickstarter campaigns in a state-quarter is related to a 0.125 (z=-2.57, p<0.05; Model 4 in Table 5) decrease in the industry concentration index of VC investment in the following state-quarter (see Figure 5).

Figure 5.
Effect of State Anti-PAE Law Enactment on the Relationship between Number of Kickstarter Campaigns and VC Industry Concentration in a State-Quarter
Note: The coefficients and 95% confidence intervals are derived from Model 4 in Table 5.

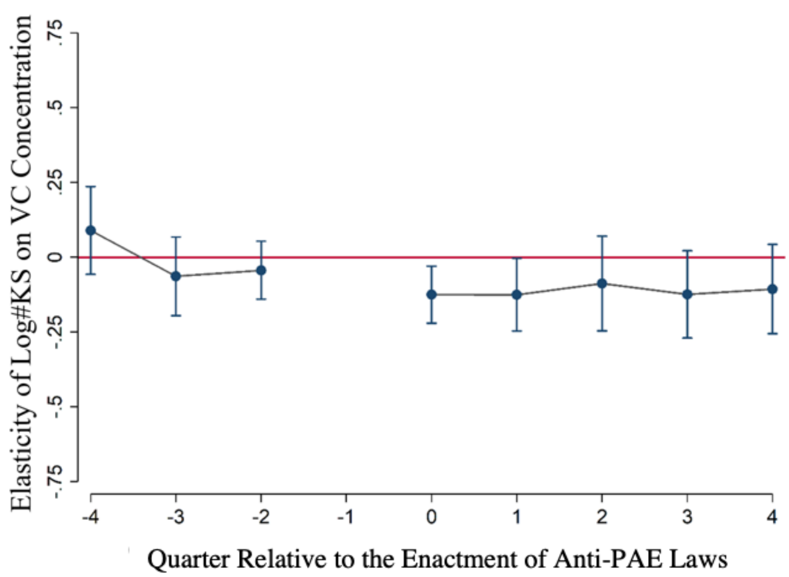


Table 5.

Effect of State Anti-PAE Law Enactment on the Relationship between Number of Kickstarter Campaigns and VC Industry Concentration in State-Quarter

	DV= VC Industry Concentration Index				
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Log KS	0.0171	0.0602*	0.224+	0.308+	0.289
	(0.91)	(2.46)	(1.92)	(1.65)	(1.35)
PAE(-4) * Log KS		0.0637	0.0549	0.0895	0.360
		(1.18)	(1.03)	(1.20)	(1.22)
PAE(-3) * Log KS		0.0239	-0.0655	-0.0635	-0.00110
		(0.45)	(-0.90)	(-0.95)	(-0.01)
PAE(-2) * Log KS		0.0180	-0.0629	-0.0436	0.0688
		(0.45)	(-1.24)	(-0.88)	(0.36)
PAE(-1) * Log KS			Omitted as baseline		
PAE(0) * Log KS		-0.0444	-0.140***	-0.125*	0.00211
		(-1.10)	(-3.44)	(-2.57)	(0.02)
PAE(1) * Log KS		-0.0374	-0.123*	-0.125*	-0.0799
		(-0.89)	(-2.16)	(-2.02)	(-0.65)
PAE(2) * Log KS		-0.0738	-0.103	-0.0876	-0.122
		(-1.45)	(-1.32)	(-1.08)	(-0.85)
PAE(3) * Log KS		-0.105*	-0.138+	-0.124+	-0.0994
		(-2.07)	(-1.95)	(-1.67)	(-0.93)
PAE(4+) * Log KS		-0.0682*	-0.135*	-0.106	-0.127
		(-2.14)	(-2.08)	(-1.40)	(-1.29)
Log GDP	-0.568	-0.507	-0.666	-0.473	-0.543
	(-0.93)	(-0.94)	(-1.26)	(-0.63)	(-0.72)
Log Income	0.707	0.585	0.413	-0.401	0.228
	(1.12)	(1.02)	(0.74)	(-0.36)	(0.21)
Log Patent	0.0188	0.0245	0.0222	0.0676	0.0722
	(0.50)	(0.64)	(0.53)	(0.79)	(0.99)
Log Patent Litigation	-0.00452	-0.00334	-0.00436	-0.0152	-0.0159
	(-0.23)	(-0.17)	(-0.23)	(-0.86)	(-0.90)
Log Self Employment	0.000286	0.00537	0.00284	-0.00168	-0.00250
	(0.01)	(0.13)	(0.07)	(-0.02)	(-0.03)
State FE	Y	Y	Y	Y	Y
Year_Quarter FE	Y	Y	Y	Y	Y
State Trend FE				Y	Y
N	881	881	881	881	910

Note: *PAE* indicators identify quarters *t*-4, *t*-3, …, *t*, …, *t*+3, and *t*>=4 for states that enact an anti-PAE law, where *t* is the quarter in which the law is enacted. States that enacted an anti-PAE law in the fourth quarter of 2016 or later, for which I observe fewer than four post-treatment observations, are excluded from the treatment group. I also exclude state-quarters with no VC investment. Robust standard errors are clustered by state. z statistics in parentheses. +p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Heterogeneous effects based on law difference. So far, I treat the existence of anti-PAE laws as a binary variable, but there is heterogeneity in these laws across states in terms of penalty (bond requirement and punitive damage remedy) and private right to take legal action (private action).

I create three binary variables to differentiate state anti-PAE laws on these two dimensions. I find consistent and robust heterogeneous effects of those laws in promoting the positive influence of Kickstarter crowdfunding activity in a state on VC investment in that state, based on Model 4 in Table 3. Penalties for PAEs show stronger effects than the private right to take legal action in terms of both attracting and diversifying VC investment in the state. Specifically, as indicated in Table 6, two quarters after the law is enacted, a 1% increase in the number of Kickstarter campaigns in a state-quarter is related to a 0.782% (bond requirement; $z=3.76$, $p<0.001$), a 0.809% (punitive damage remedy; $z=3.7$, $p<0.001$), or a 0.242% (private action; $z=1.06$, $p>0.1$) increase in the number of VC investments in the following state-quarter. For VC investment concentration, once the anti-PAE laws are enacted, a 1% increase in the number of Kickstarter campaigns in a state-quarter is related to a 0.177% (bond requirement; $z=-2.76$, $p<0.01$), a 0.191% (punitive damage remedy; $z=-2.63$, $p<0.01$), or a 0.128% (private action; $z=-1.73$, $p<0.1$) decrease in the industry concentration index of VC investment in the following state-quarter.

Table 6.

Effect of State Anti-PAE Law Difference on the Relationship between Kickstarter Campaigns and VC Investment in State-Quarter

	DV= Log (# VC Investments)			DV= VC Industry Concentration Index		
Variable	**Bond**	**Remedy**	**Private**	**Bond**	**Remedy**	**Private**
Log KS	-0.381	-0.405	-0.210	0.328	0.370	0.337
	(-1.28)	(-1.09)	(-0.57)	(1.50)	(1.56)	(1.51)
PAE(-4) * Log KS	-0.506	-0.504	-0.461	0.253*	0.267+	0.184
	(-1.25)	(-0.91)	(-1.44)	(2.14)	(1.78)	(1.20)
PAE(-3) * Log KS	0.168	0.227	0.0480	-0.0324	-0.128	-0.0895
	(0.39)	(0.57)	(0.17)	(-0.20)	(-0.85)	(-0.81)
PAE(-2) * Log KS	-0.196	0.114	0.0492	-0.0676	-0.0563	-0.0461
	(-0.61)	(0.32)	(0.17)	(-0.72)	(-0.59)	(-0.63)
PAE(-1) * Log KS	Omitted as baseline					
PAE(0) * Log KS	0.266	0.321	0.0757	-0.177**	-0.191**	-0.128+
	(1.62)	(1.53)	(0.42)	(-2.76)	(-2.63)	(-1.73)
PAE(1) * Log KS	0.347*	0.318+	0.0369	-0.174+	-0.207+	-0.137
	(2.21)	(1.86)	(0.16)	(-1.86)	(-1.92)	(-1.38)
PAE(2) * Log KS	0.782***	0.809***	0.242	-0.118	-0.133	-0.132
	(3.76)	(3.39)	(1.06)	(-0.93)	(-1.09)	(-1.52)
PAE(3) * Log KS	0.728***	0.792***	0.467*	-0.163	-0.213*	-0.121
	(5.07)	(4.19)	(1.97)	(-1.53)	(-2.11)	(-1.26)
PAE(4+) * Log KS	0.224	0.307	0.0230	-0.0695	-0.105	-0.0641
	(1.26)	(1.40)	(0.11)	(-0.47)	(-0.79)	(-0.60)
Log GDP	0.348	0.359	0.443	-0.393	-0.347	-0.340
	(0.35)	(0.36)	(0.45)	(-0.49)	(-0.43)	(-0.43)
Log Income	0.0142	0.113	0.0522	0.0742	-0.00937	-0.121
	(0.01)	(0.07)	(0.03)	(0.07)	(-0.01)	(-0.11)
Log Patent	0.147*	0.135*	0.144*	0.0752	0.0827	0.0776
	(2.21)	(2.03)	(2.15)	(0.82)	(0.92)	(0.85)
Log Patent Litigation	0.0228	0.0204	0.0187	-0.0141	-0.0164	-0.0145
	(0.73)	(0.64)	(0.59)	(-0.77)	(-0.88)	(-0.80)
Log Self	-0.109	-0.107	-0.0944	0.00531	0.0127	0.0106
	(-0.87)	(-0.81)	(-0.73)	(0.07)	(0.18)	(0.15)
State FE	Y	Y	Y	Y	Y	Y
Year_Quarter FE	Y	Y	Y	Y	Y	Y
State Trend FE	Y	Y	Y	Y	Y	Y
N	1500	1500	1500	881	881	881

Note: *PAE* indicators identify quarters *t*-4, *t*-3, …, *t*, …, *t*+3, and *t*>=4 for states that enact a specific dimension (i.e., bond, remedy, private) of an anti-PAE law, where *t* is the quarter in which that dimension is enacted. States that enacted an anti-PAE law in the fourth quarter of 2016 or later, for which I observe fewer than four post-treatment observations, are excluded from the treatment group. Robust standard errors are clustered by state. z statistics in parentheses. +p<0.10, * p<0.05, ** p<0.01, *** p<0.001.

Discussion

Conclusion. This study introduces the idea that crowdfunding platforms are a source of signals for VCs but also for PAEs. It provides evidence that signals from crowdfunding platforms on entrepreneurial activity can attract VC investment when the risk of PAEs is mitigated by anti-PAE laws. The signals also diversify the flow of VC investment across industries. Finally, this study reveals that these benefits of crowdfunding platforms are better safeguarded by anti-PAE laws that impose penalties (bond requirement and punitive damage remedy) than by those that provide the private right to take legal action.

Contribution. This study contributes to an emerging research stream on how crowdfunding interacts with professional investors such as VCs in democratizing financing for innovation and entrepreneurship. The current scholarly conversation indicates that the high-quality signals from entrepreneurial campaigns on crowdfunding platforms empower VCs to evaluate entrepreneurs' ability and to assess demand prior to the launch of a new product. As a result, crowdfunding makes entrepreneurs more visible to professional investors and democratizes entrepreneurs' access to such investment. However, as documented in this study, the signals from entrepreneurial campaigns on crowdfunding platforms are also available to PAEs, so that the benefit of crowdfunding comes with risk. This study addresses that tension, extending the research framework for understanding the benefit of crowdfunding platforms with respect to democratizing entrepreneurial financing by introducing the perspective of IPR risk and how it can be regulated through institutional governance to enjoy the benefits of crowdfunding.

This study also informs a debate among policy makers on the benefits and costs of PAEs to the economy (Federal Trade Commission 2016) by presenting evidence that state anti-PAE policy is critical in realizing two benefits from crowdfunding platforms: attracting VC investment into the state and diversifying it across industries within the state. While I focus on a reward-based crowdfunding platform—Kickstarter—my results also have implications for equity-based crowdfunding. Policy makers have enacted a number of laws and regulations for equity-based crowdfunding, such as the Jumpstart Our Business Startups (JOBS) Act, to expand companies' access to entrepreneurial finance, hoping that the funded companies will create jobs and spur economic growth. To protect retail investors, the US Security and Exchange Committee requires companies that seek equity-based crowdfunding to disclose information ranging from a business description to financial information to the management team. Such disclosure, however, provides opportunities for PAEs to evaluate infringement against their patent portfolios. In addition, equity-based crowdfunding campaigns tend to have deeper pockets, which make them more attractive to cash-hungry PAEs (Cohen et al. 2016). Therefore, policy makers face a dilemma. On one hand, they need to design policies to reduce information asymmetry between retail investors and funded companies by requiring more disclosure. On the other hand, more disclosure increases the risk from PAEs. This study indicates that state anti-PAE laws are a promising solution.

Limitations and future research. One should be careful in interpreting these findings, in light of some limitations. First, I am unable to observe PAEs' behavior of sending demand letters. As a result, the underlying mechanism that drives the results could come because anti-PAE laws reduce the number of demand letters or because they decrease the severity of the threat as perceived by entrepreneurs or VCs or both. Second, while anti-PAE laws can potentially increase the quantity of information disclosed by entrepreneurs on crowdfunding platforms and incentivize VCs to invest in the state, I do not have the data with which to provide empirical evidence of such benefits from anti-PAE laws. Third, my results do not address the long-term effects of anti-PAE laws in promoting the influence of a state's crowdfunding activity on VC investments in that state. The long-term effect disappears when I include state-specific linear trends in the model. One possible explanation is that the effect of anti-PAE laws is still there but is absorbed in the state trend a few quarters after the laws are enacted. As I do not provide direct empirical evidence corresponding to this explanation, I do not claim a long-term effect. Future research can enrich my findings by (a) providing project-level evidence by identifying Kickstarter projects that received VC investment, (b) exploring how anti-PAE laws affect the information disclosure and VC investment incentive to illuminate the underlying mechanism, and (c) examining the effects of anti-PAE laws on different types of VC investment (corporate vs. independent).

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